

For which patients shall the drug work, and how?

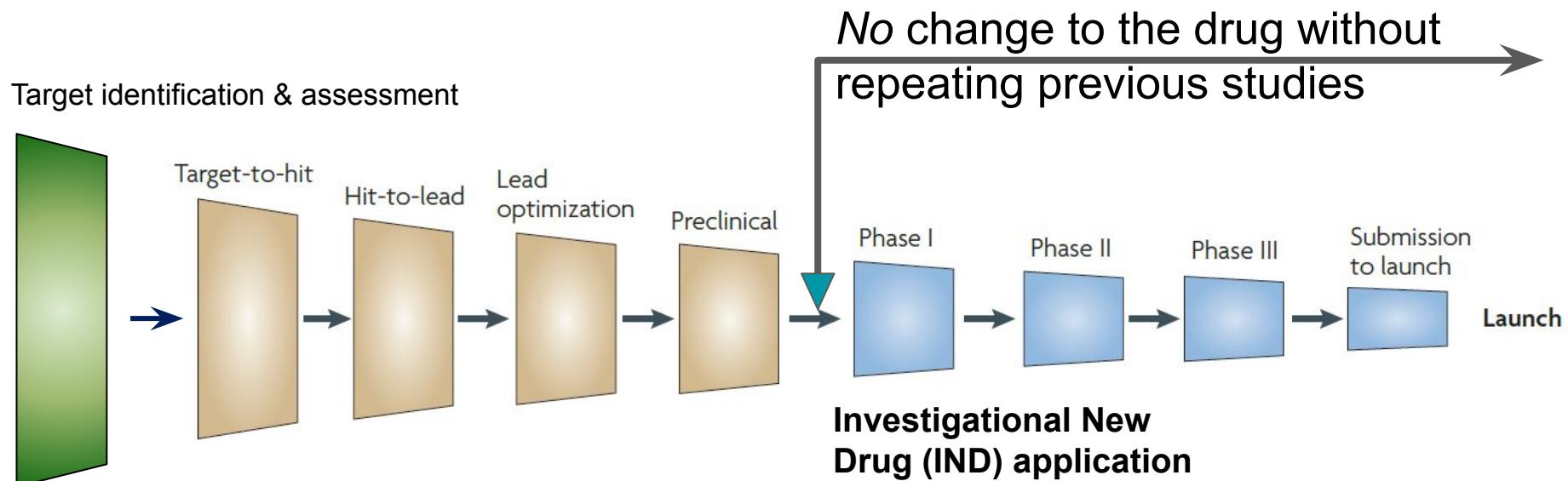
Mathematical and Computational Biology in Drug Discovery (MCBDD)
Module V

Dr. Jitao David Zhang
May-June 2021

Outline of Module V

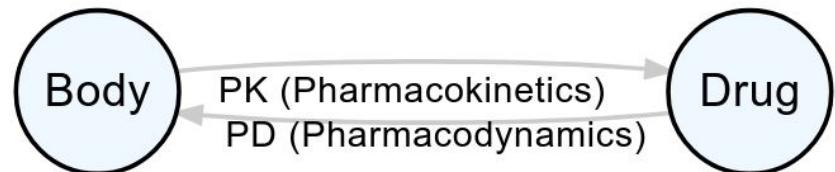
- Lecture 11
 - Biomarker for dose prediction
 - Biomarker for patient-stratification and biology understanding: Merck/Genentech
 - Challenges and caveats
- Lecture 12
 - Integrating statistical and mechanistic modelling: Griffiths *et al.*
 - Mechanistic modelling of biological systems: from Boolean network to Agent-based modelling
 - Causal inference

From drug discovery to drug development

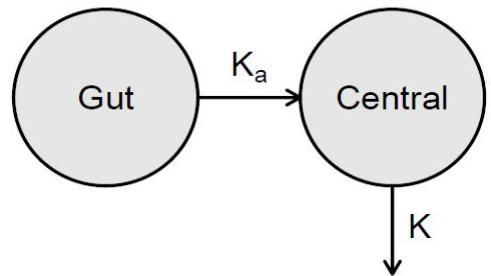


A refresher of PK/PD Modelling

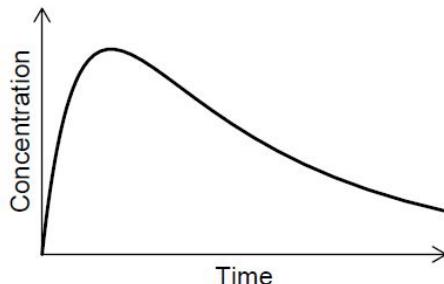
(A)



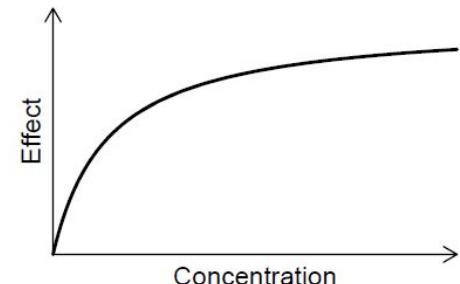
(B)



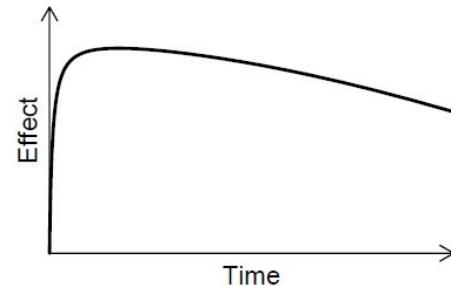
(C)



(a) PK model



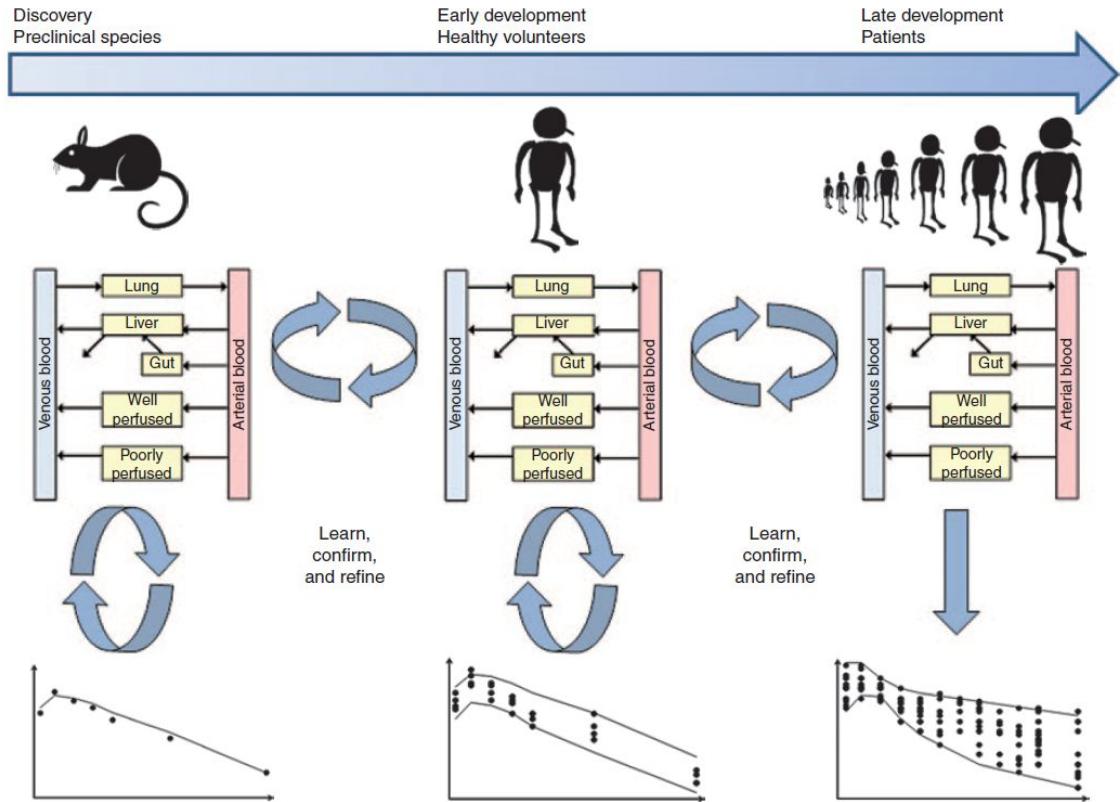
(b) PD model



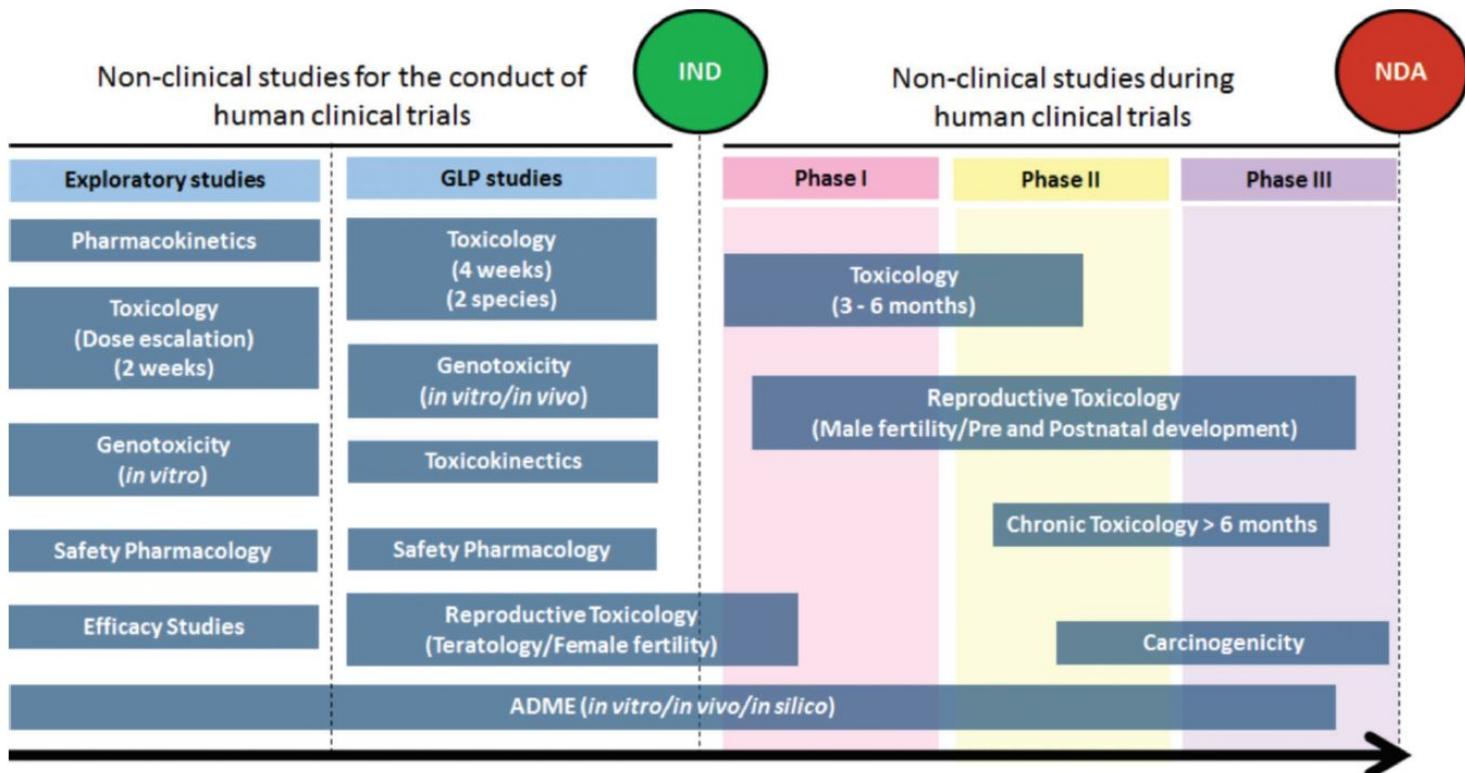
(c) Combined PK/PD model

$$A_{oral}(t) = \frac{K_a F A_0}{K_a - K} (\exp(-K \cdot t) - \exp(-K_a \cdot t))$$

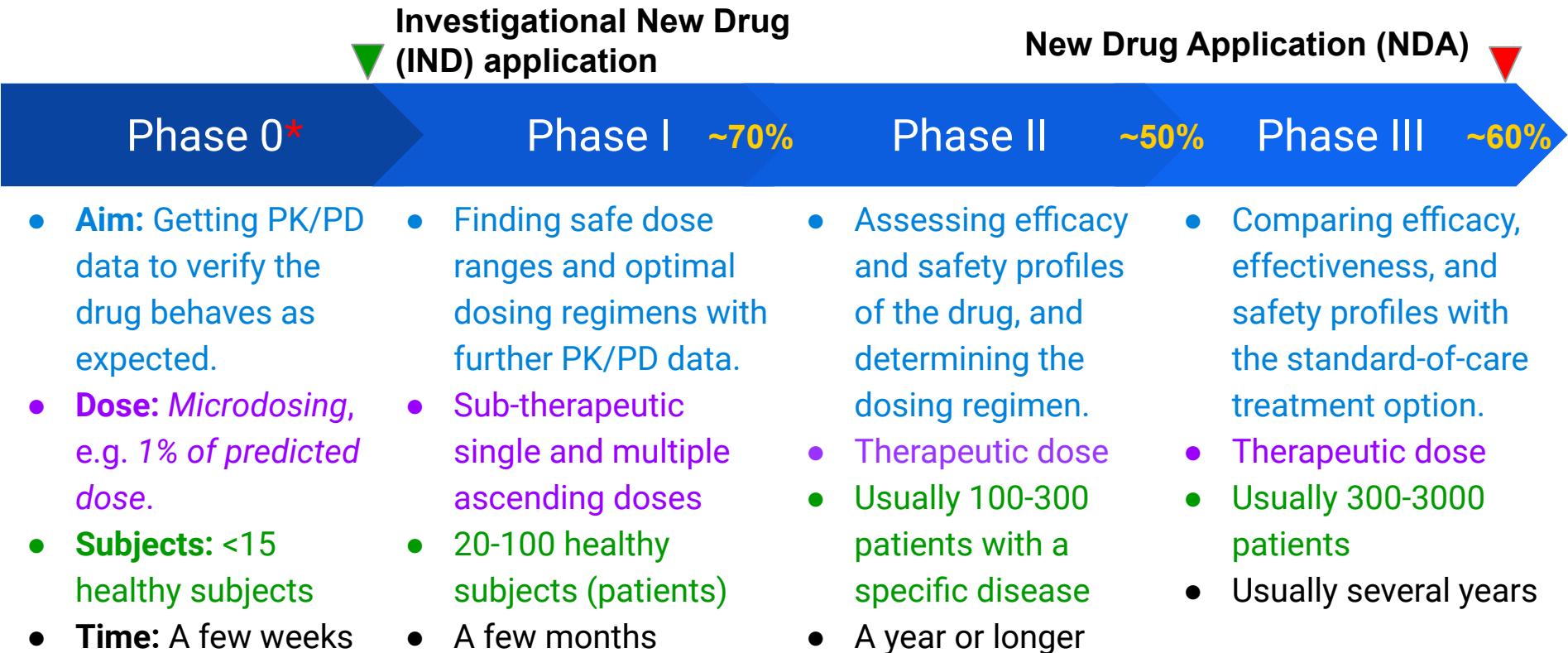
Physiologically-based pharmacokinetic modelling (PBPK) is a natural extension of PK modelling



Non-clinical studies continue during drug development



Phases of clinical trials



Empirical, stratified, and individualized medicine



Empirical medicine

- Vaccines
- Non-steroid anti-inflammatory drugs (NSAIDs)

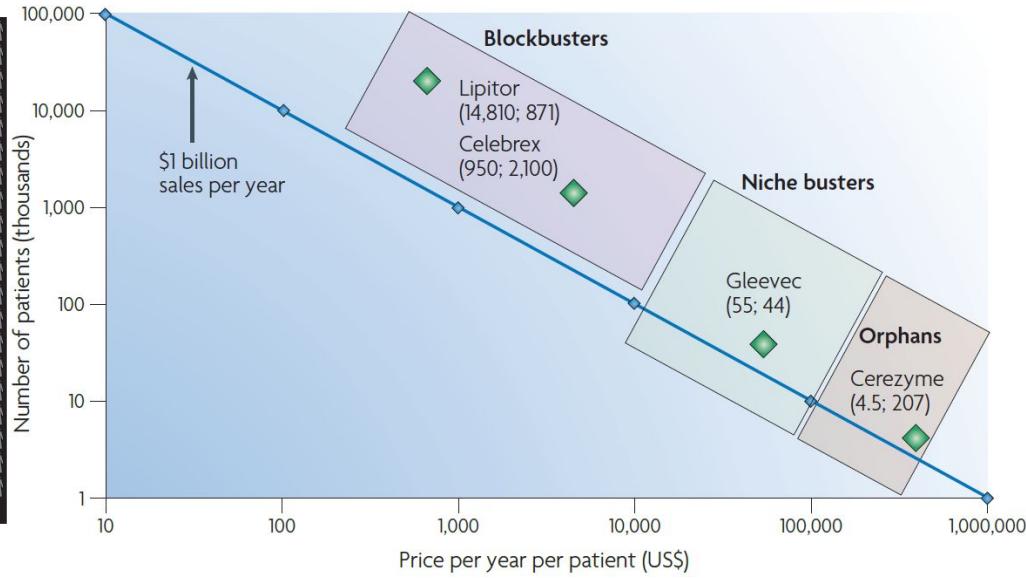
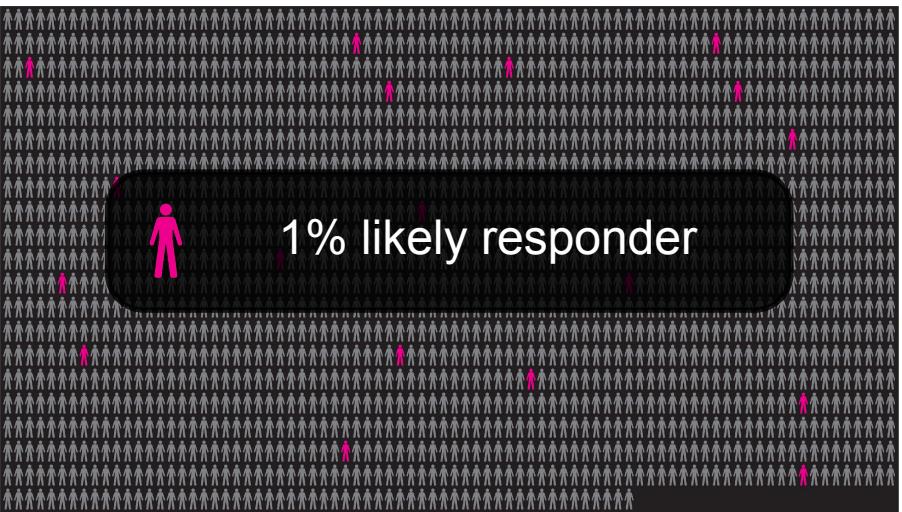
Stratified Medicine

- Vemurafenib (Zelboraf)
- Trastuzumab (Herceptin)

Individualized medicine

- CAR-T therapy

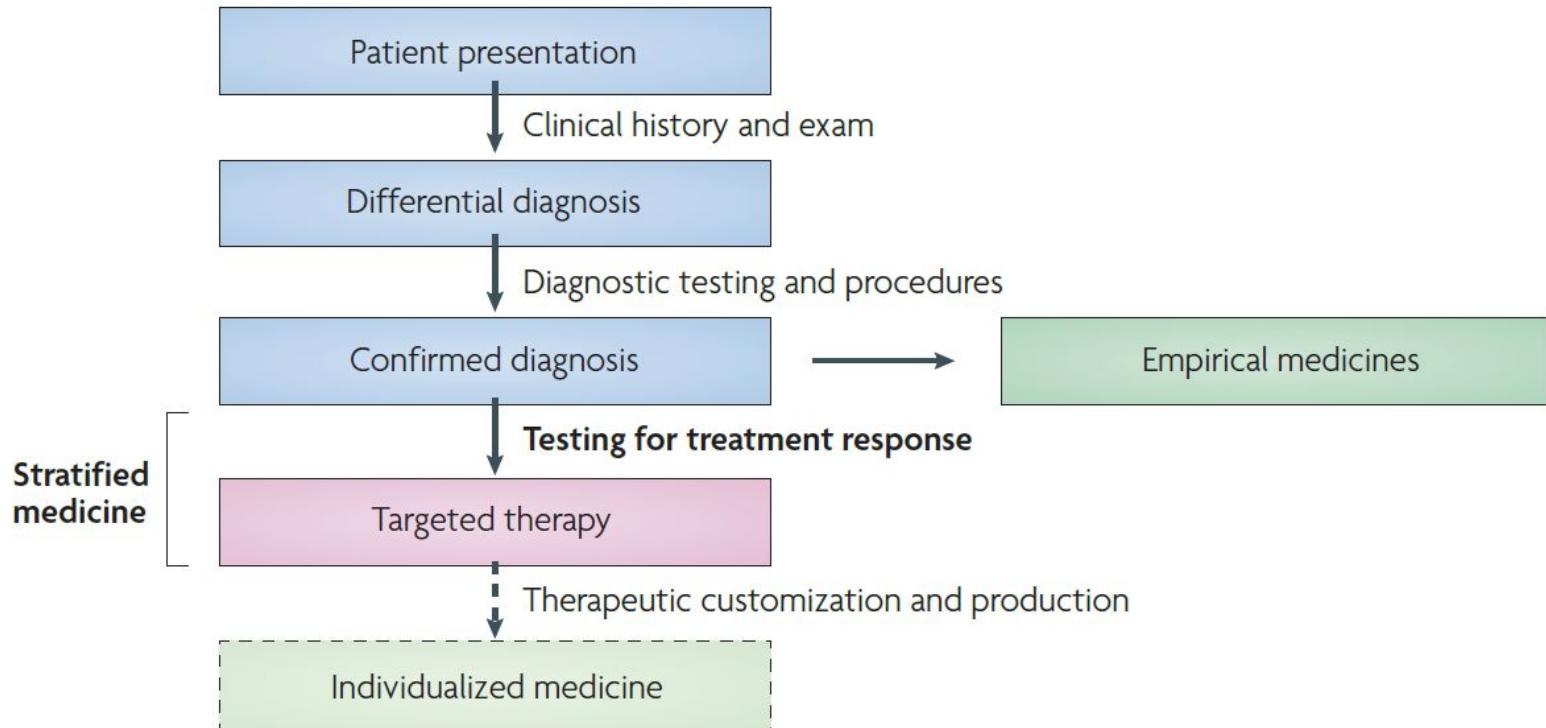
Why stratified medicines are becoming popular?



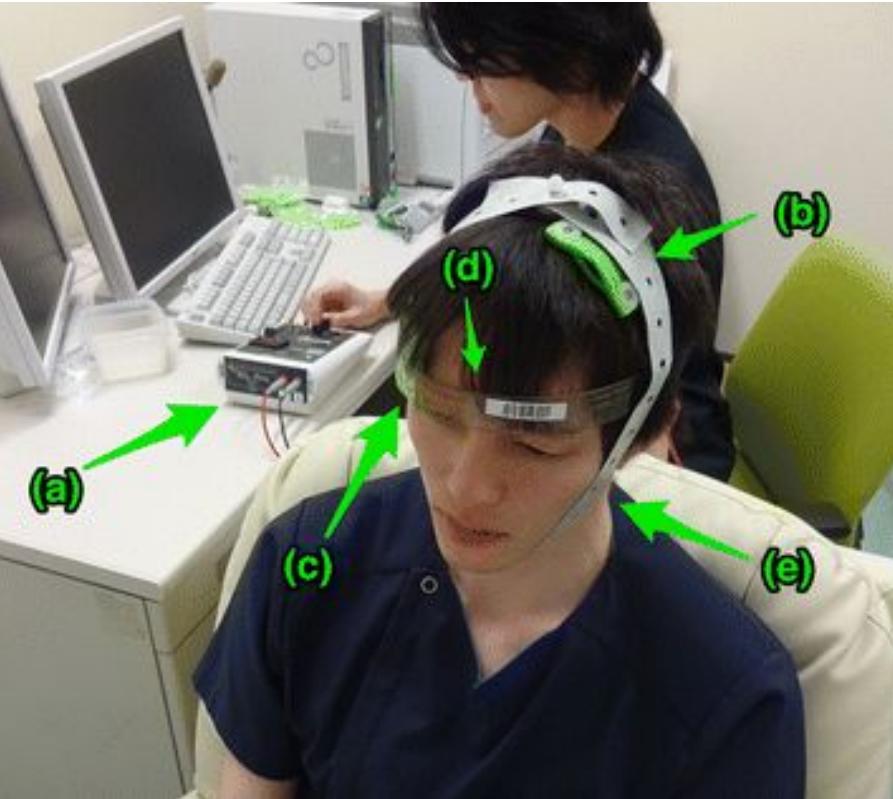
Medical reasons

Commercial reasons

Empirical, stratified, and individualized medicine in the clinical context



Transcranial Direct Current Stimulation (tDCS)



Transcranial Direct Current Stimulation (tDCS)

LIFTID tDCS Gerät zur Verbesserung von Fokus, Aufmerksamkeit, Gedächtnis und Produktivität

Marke: LIFTID

Preis: **169,00 €**

Preisangaben inkl. USt. Abhängig von der Lieferadresse kann die USt. an der Kasse variieren. [Weitere Informationen](#).

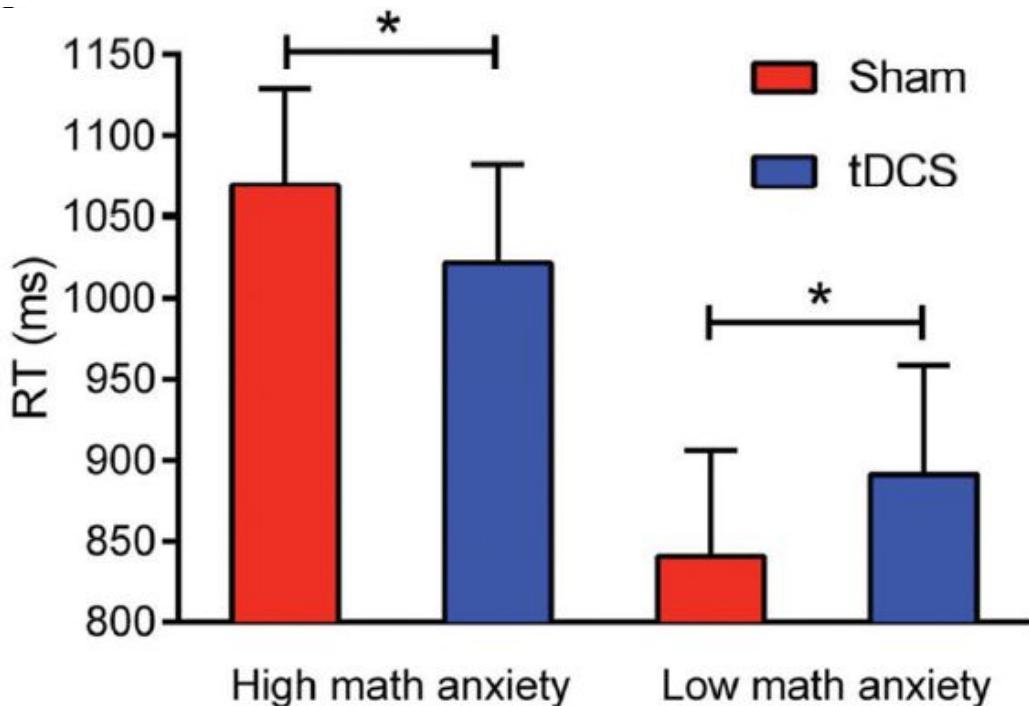
Ausgaben im Blick behalten und **8€ Aktionsgutschein** sichern: Jetzt Amazon-Konto aufladen [Mehr erfahren](#)



- Verbessern Sie Ihre Leistung: Entwickelt für Gamer, Studenten, vielbeschäftigte Profis, Musiker und Sportler. Jeder kann LIFTID verwenden, um seine Leistung zu erhöhen, es dauert nur 20 Minuten, um LIFTID während Ihrer Lieblingsaufgabe zu verwenden.
- tDCS leicht gemacht: leicht (nur 70 Gramm), keine Kabel und einfach zu bedienen (Plug 'n Play). Einfach die Pads anfeuchten, aufsetzen und losdrücken. Gerät läuft automatisch für 20 Minuten bei 1,2 mA.
- Reisesicher: Wiederaufladbarer, langlebiger Lithium-Ionen-Akku. Vergessen Sie die Suche nach einem 9V Akku, der LIFTID Gerät Akku ist langlebig und schnell zu laden. Liftid ist eine Freisprecheinrichtung und benötigt keine Basiseinheit. Absolut tragbar. Verwenden Sie es beim Sitzen, Stehen, Gehen oder Dehnen.

Not tested in randomized clinical trials
(<https://clinicaltrials.gov>)

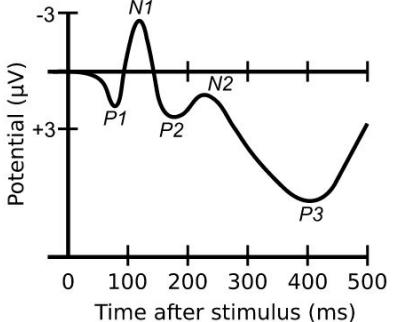
Cognitive Enhancement or Cognitive Cost? It depends!



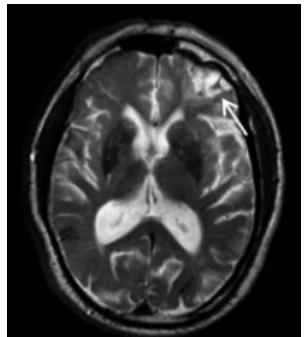
Biomarkers

A objectively measured and evaluated characteristic as an indicator of (1) normal biological process, (2) pathogenic processes, or (3) pharmacological responses to a therapeutic intervention.

Electro-physiological



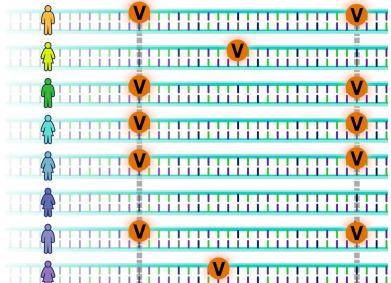
Imaging



Functional

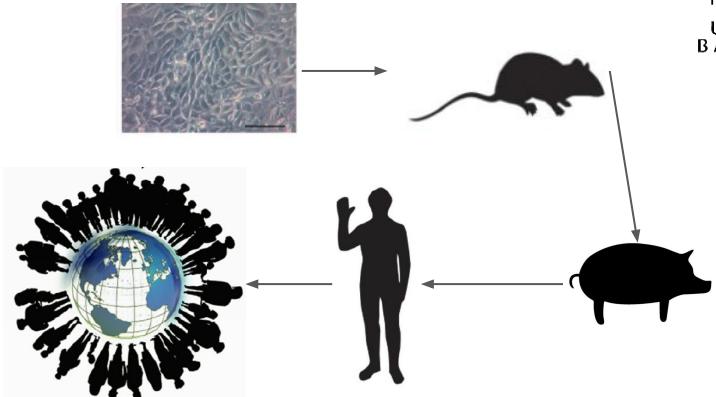


Molecular



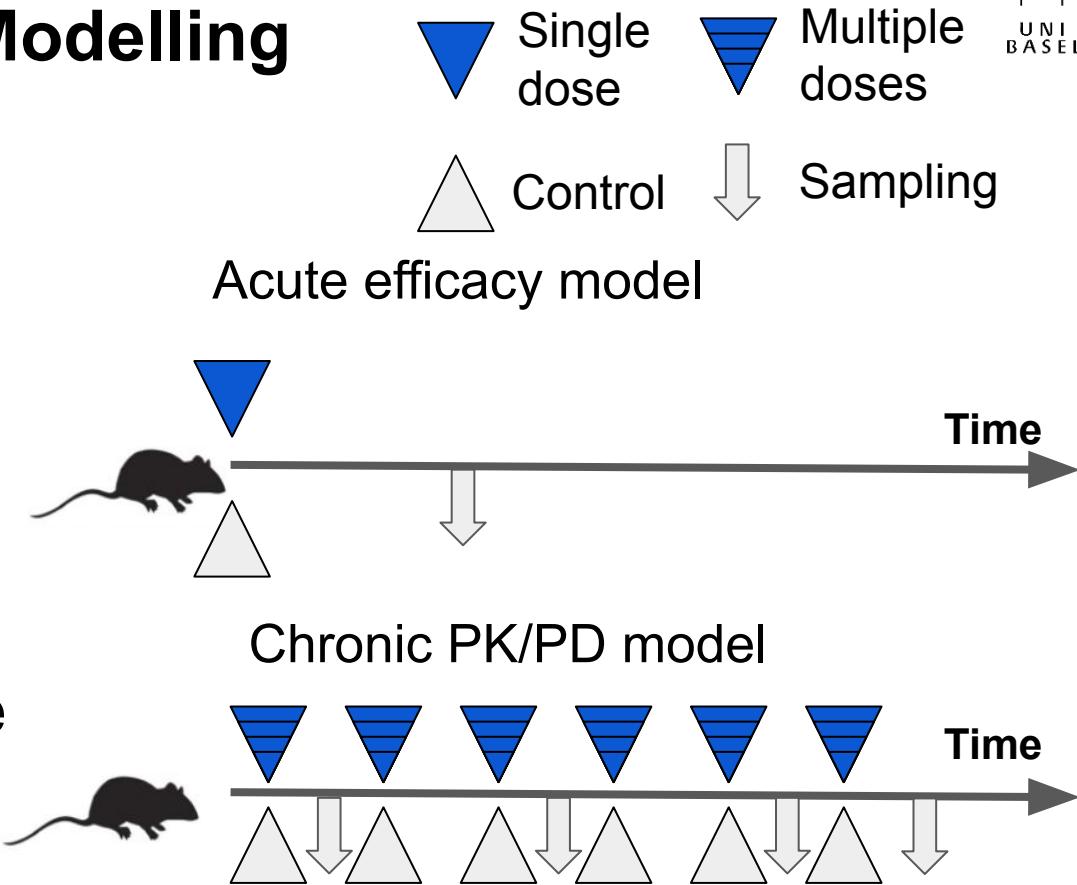
Applications of biomarkers

1. Compound optimization and differentiation from competitors in preclinical study
2. Human-dose prediction in translational PK/PD modelling
3. Patient stratification in clinical studies



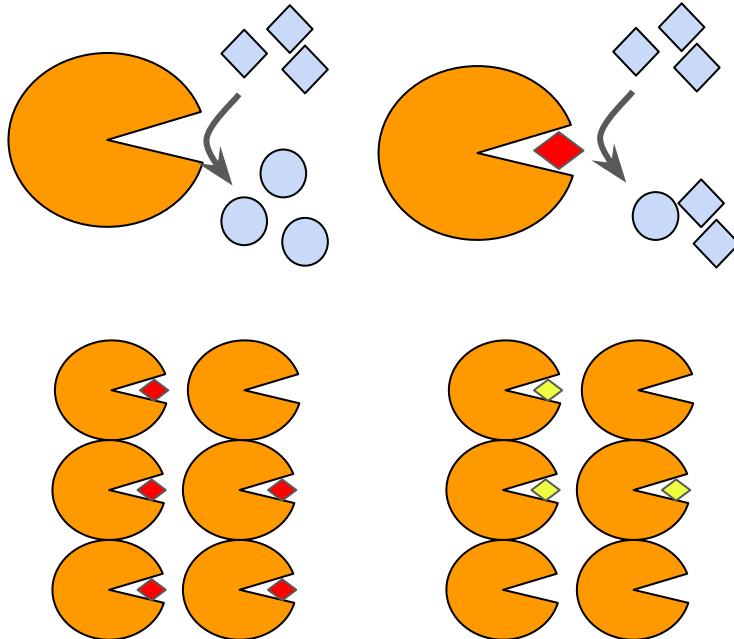
Translational PK/PD Modelling

Samples from blood and the target organ can be analysed for pharmacokinetics, pharmacodynamics, and dose-exposure-response relationships.



Target Occupancy as Biomarkers

Target occupancy, percentage of the protein target occupied by drugs, affects **target engagement**, which describes the process a drug interacts with its intended protein target in a living system to induce downstream effects (Mechanism of Action).

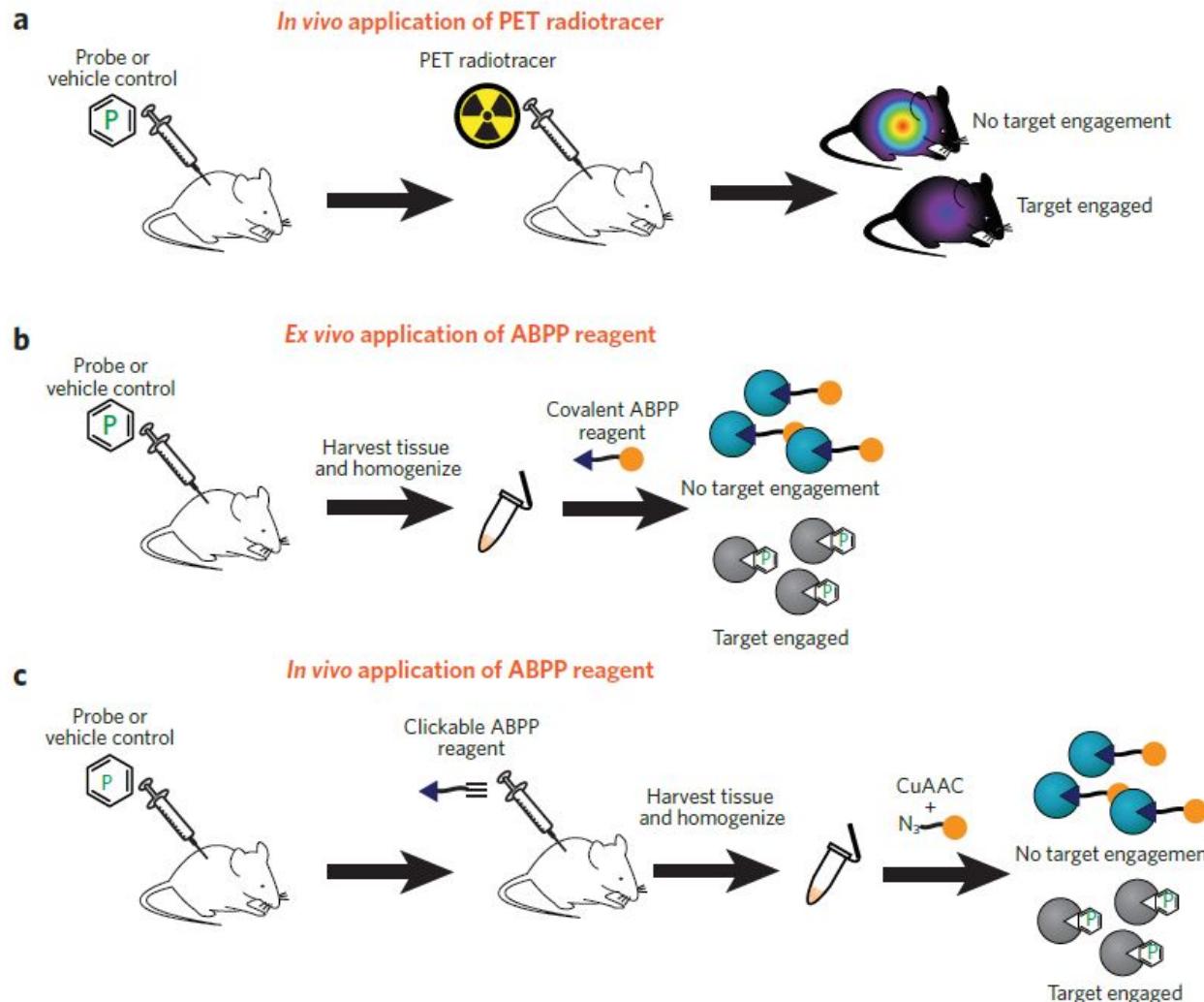


Target occupancy of 83% and 50%, respectively

Target occupancy and engagement profiling in vivo

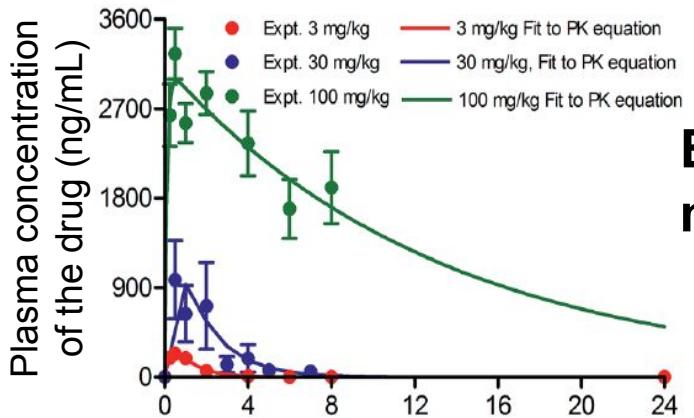
ABPP: Activity-based protein profiling; PET: positron-emission tomography.

Both ABPP reagent and radiotracer binds to the same protein target.

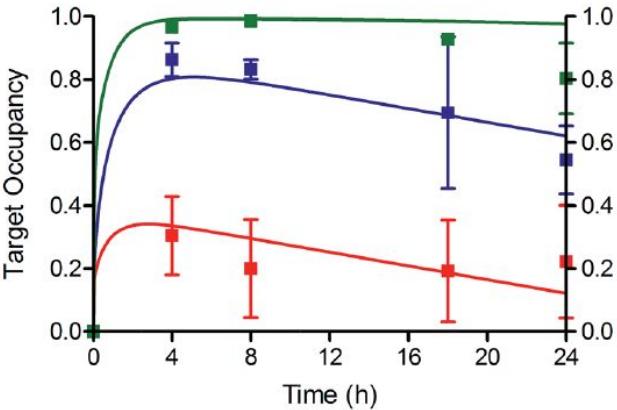


Target occupancy as a biomarker links pharmacokinetics and pharmacodynamics

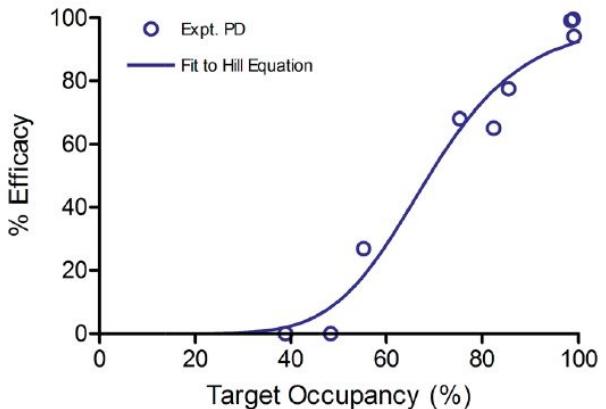
PK modelling



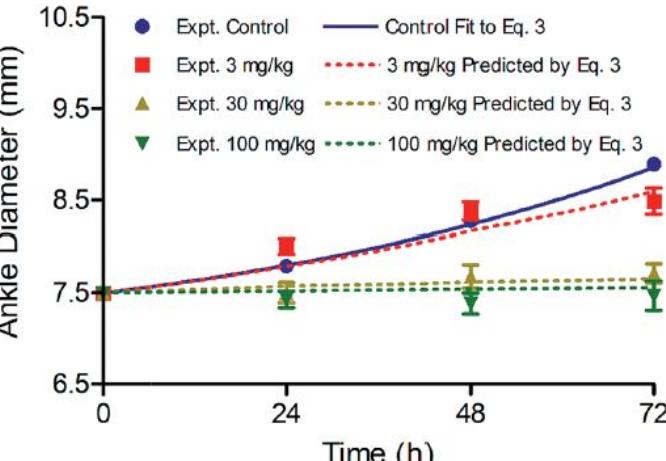
Biomarker modelling



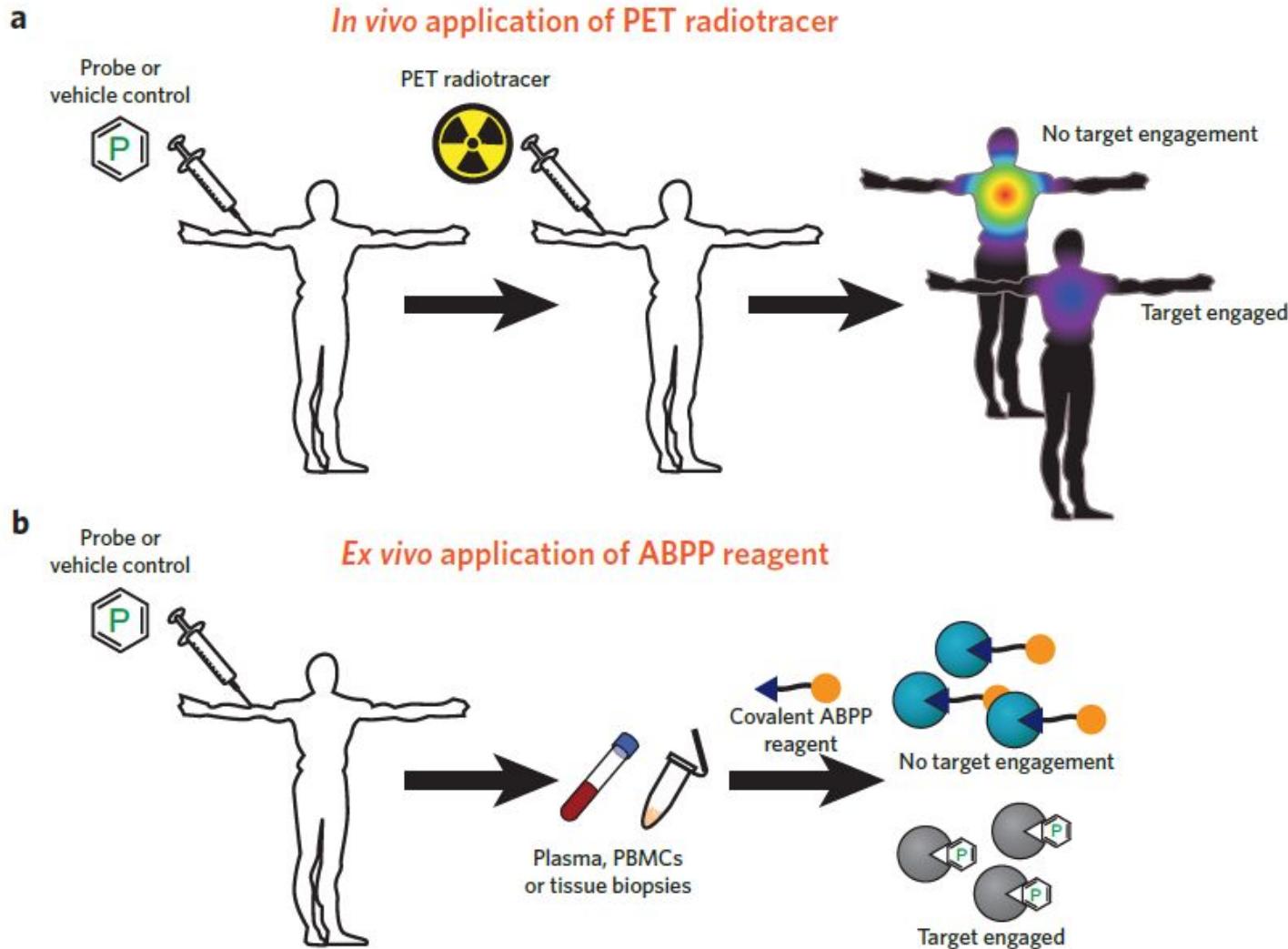
PD modelling



PK/PD modelling



Target occupancy and engagement profiling in human

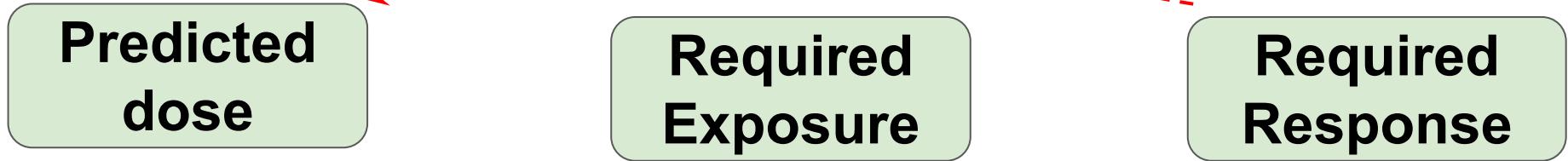


A mental model of biomarker for human-dose prediction

Animal model

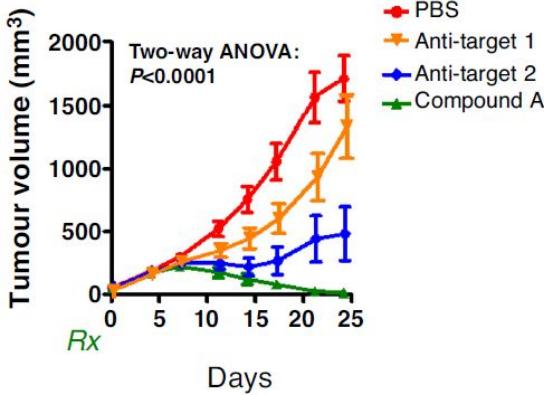


Translational biomarker
(e.g. Target occupancy in PBMC and in tumour)

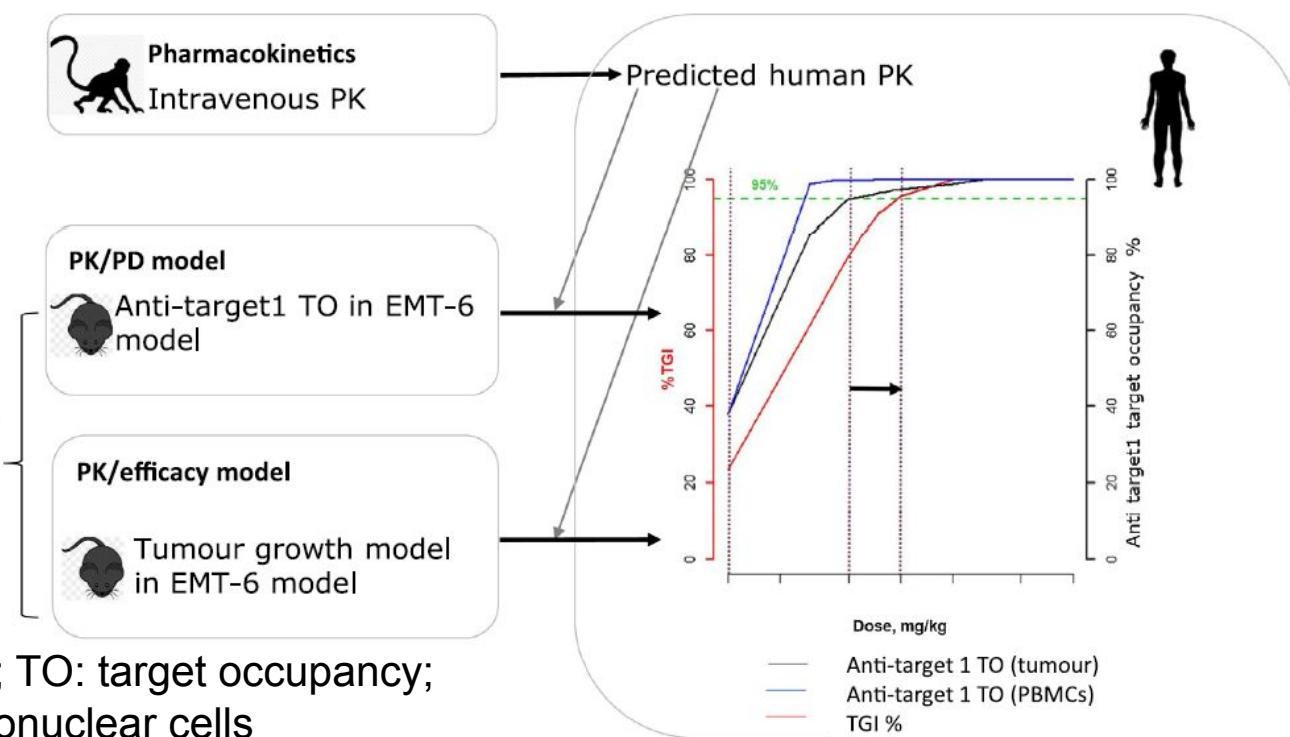


Human

A real-word example with a bispecific antibody



Anti-target 1 TO required for efficacy in tumour and PBMCs
 Efficacious concentration



TGI: tumour growth inhibition; TO: target occupancy;
 PBMC, peripheral blood mononuclear cells

Exposure-response in animal model and translatable biomarkers are essential for dose prediction

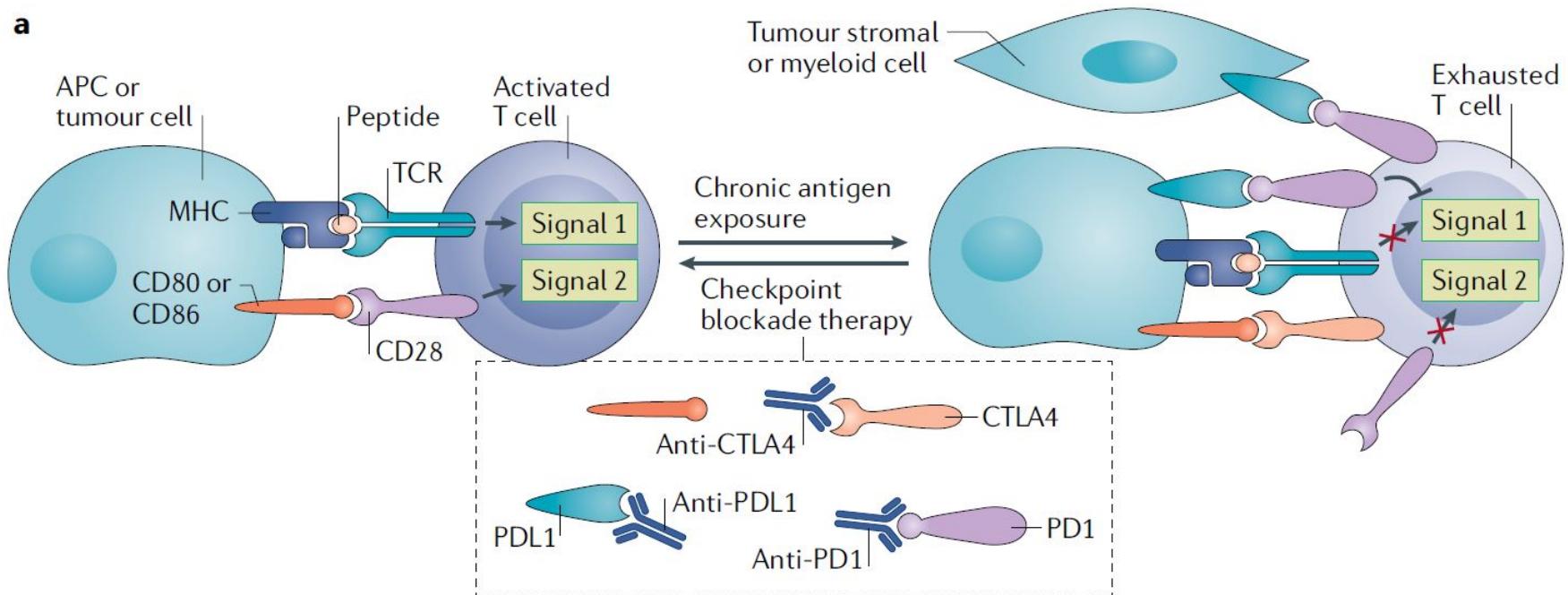
TABLE 2

Correlation of responses to dose-related questions (Q) of TmX Guide to dose prediction successes or observation of efficacy in the clinic

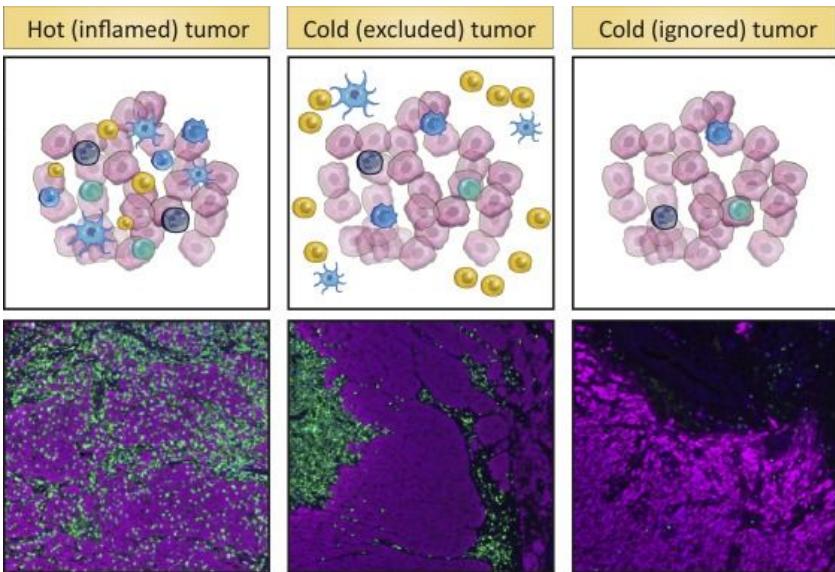
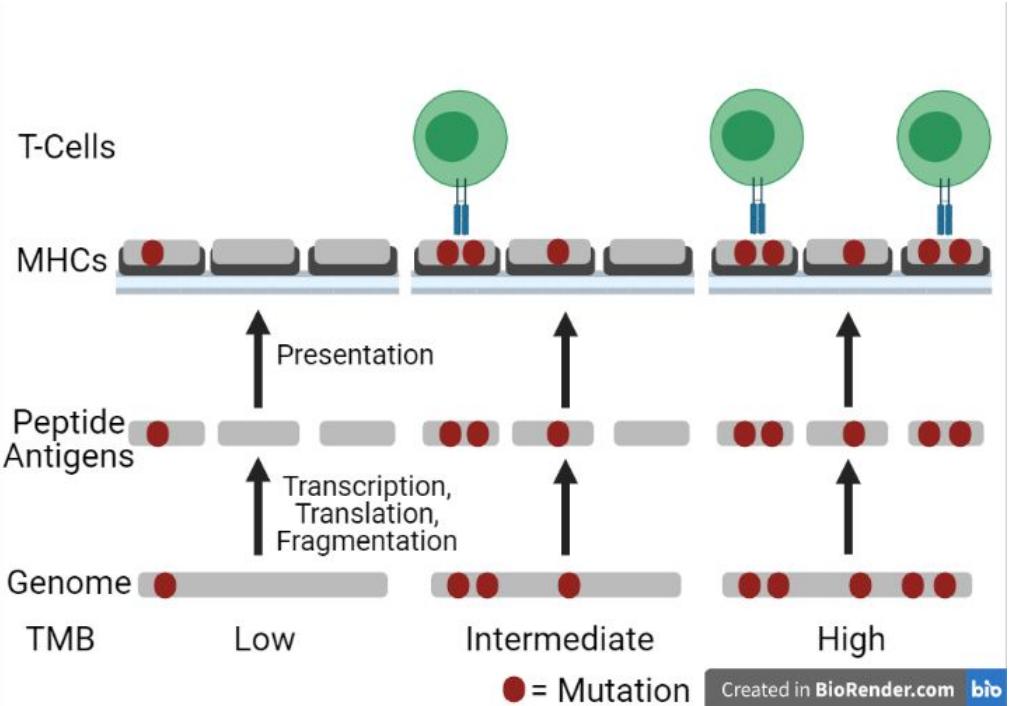
Category	Q1: desired exposure-response in appropriate animal model?	Q2: Translatable biomarkers?	Number of drugs for which model-based active dose prediction is within twofold or clinical efficacy is observed within predicted dose range out of total number in category
1	Yes	Yes	5/6
2 ^a	No	No	1/6
3	No	Yes	2/2
4 ^b	Yes	No	0/1

Molecular basis of cancer immunotherapy

a



Tumour mutation burden and immune phenotype may affect the effect of immunotherapy

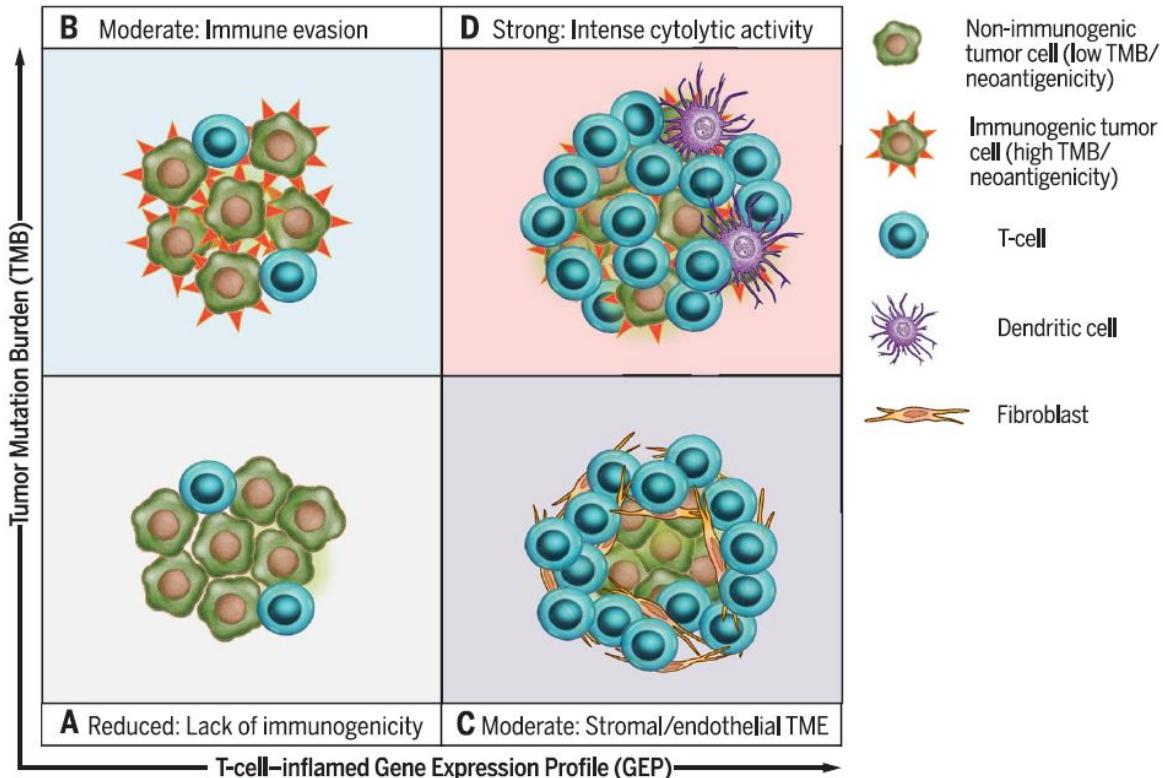


Trends in Cancer

MHC: Major Histocompatibility Complex; TMB: Tumour Mutation Burden.

Cristescu et al. established TMB and T-cell-inflamed Gene Expression Profile (GEP) as biomarkers

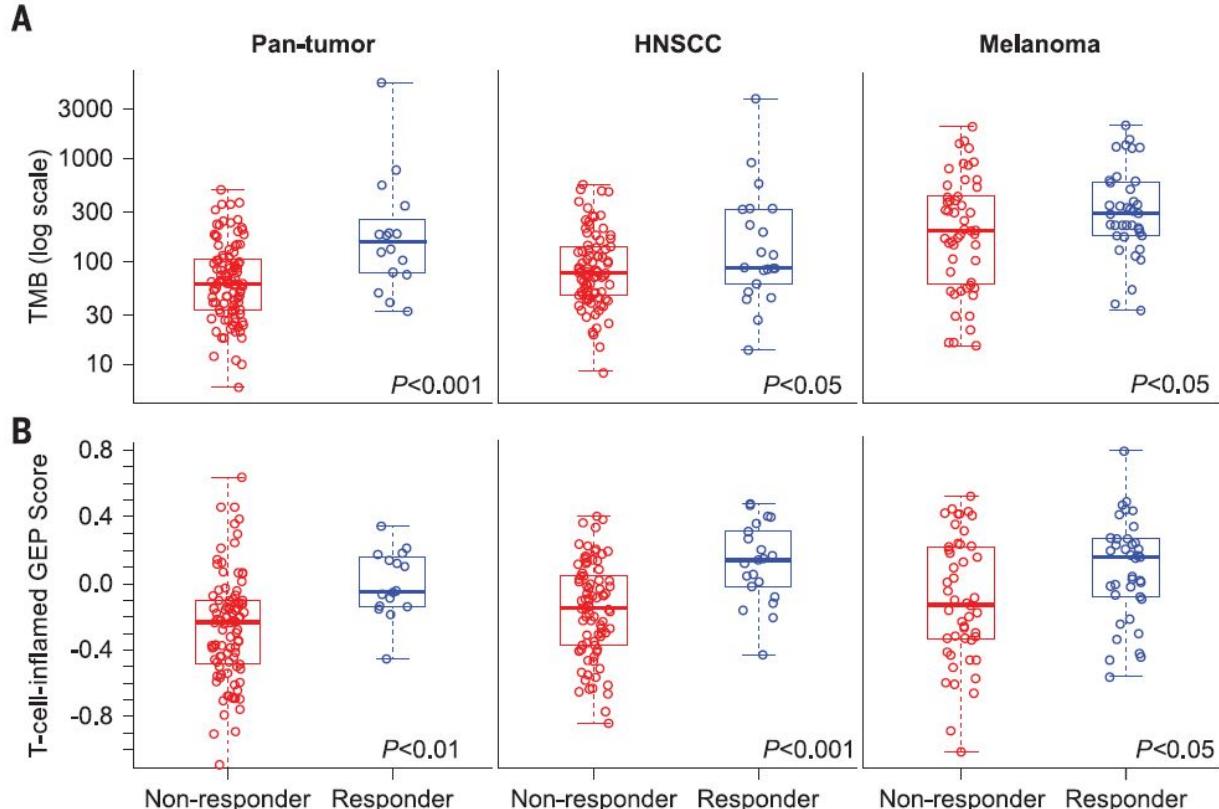
Patients with high tumor mutation burden **AND** a T-cell-inflamed gene expression profile (TME) are more likely to respond to cancer immunotherapy.



Univariate analysis establishes correlation between TMB/GEP and responsiveness

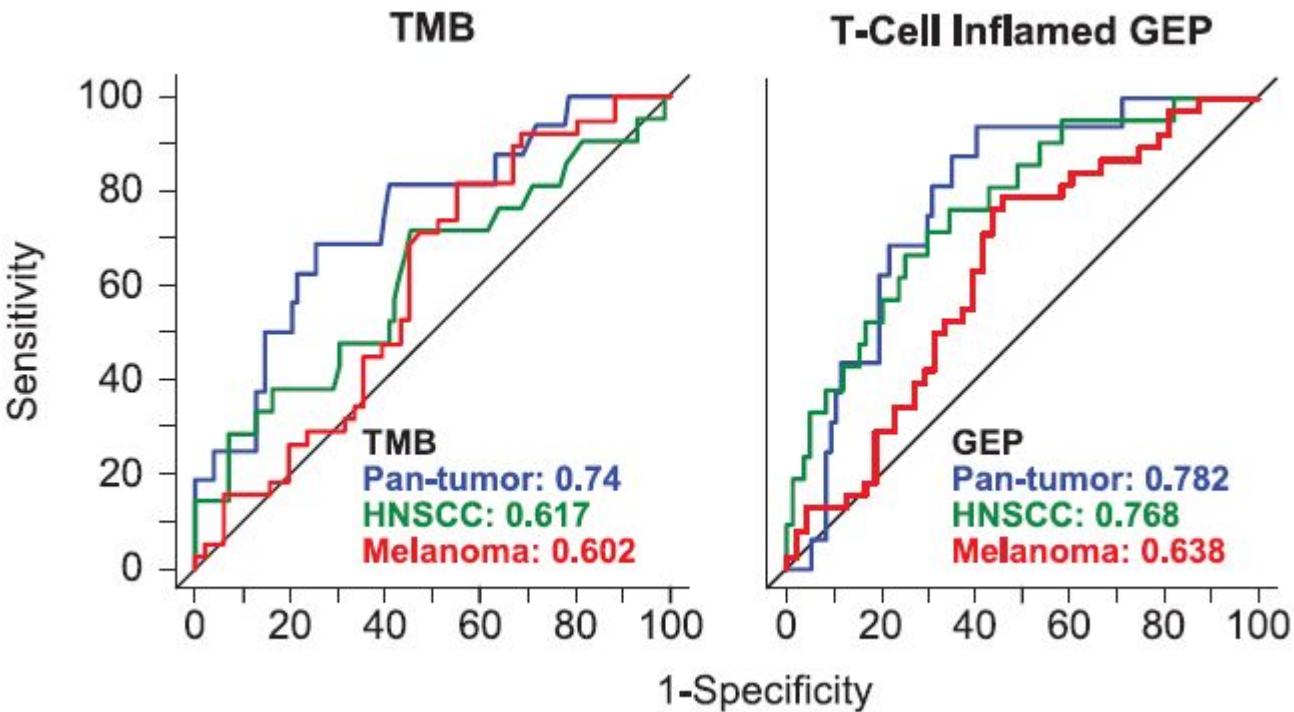
GEP: weighted sum of normalized expression of 18 genes related with immune response (CCL5, CD27, CD274 (PD-L1), CD276 (B7-H3), CD8A, CMKLR1, CXCL9, CXCR6, HLA-DQA1, HLA-DRB1, HLA-E, IDO1, LAG3, NKG7, PDCD1LG2 (PDL2), PSMB10, STAT1, and TIGIT).

HNSCC: head and neck cancer



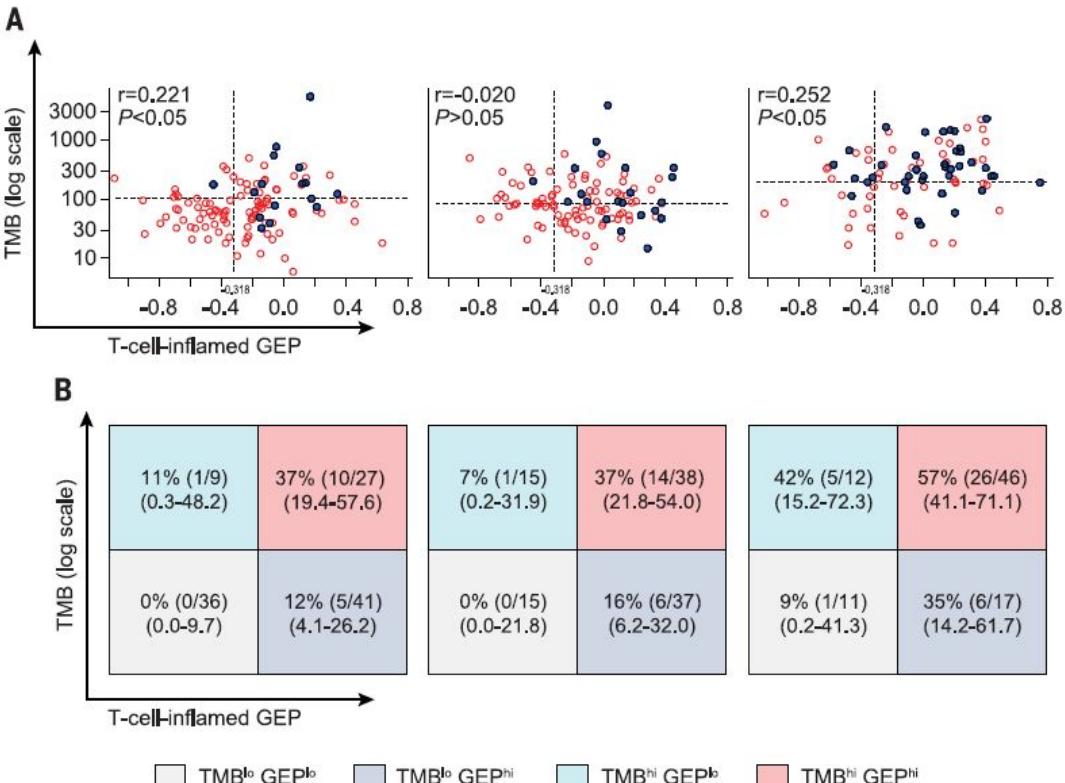
Both TMB and GEP can partially predict responsiveness

Receiver
 Operating
 Characteristic
 (ROC) curves of
 using either TMB
 or GEP for binary
 classification.
 Metrics: Area
 Under ROC
 (AUROC)

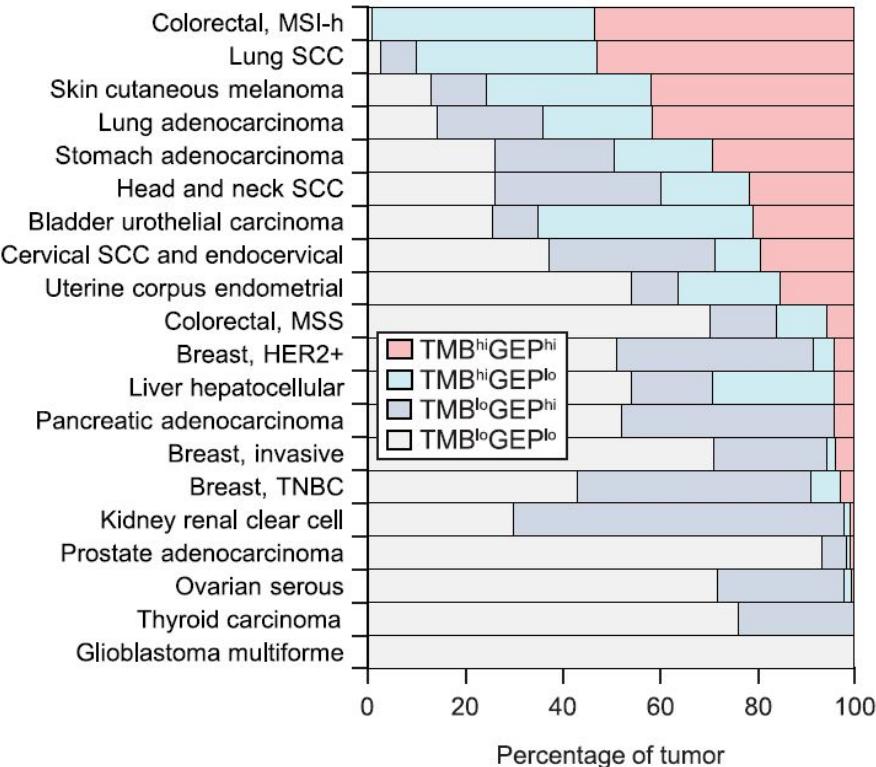
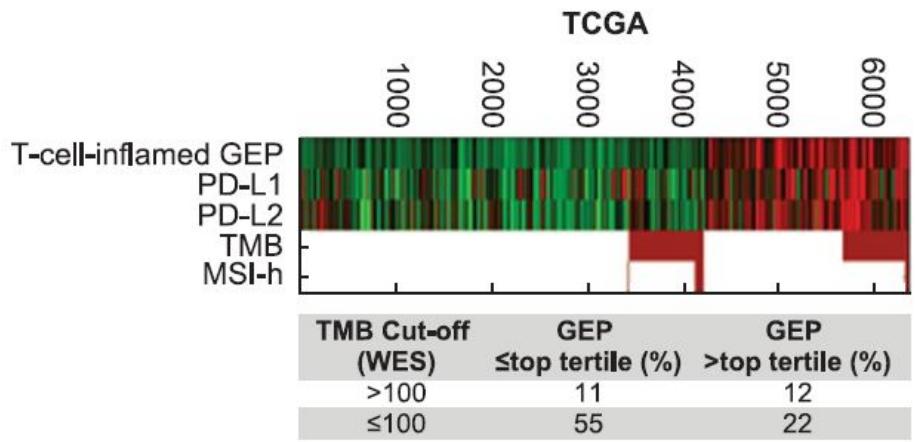


High TMB and high GEP are associated with higher responsiveness to anti-PD1 antibody treatment

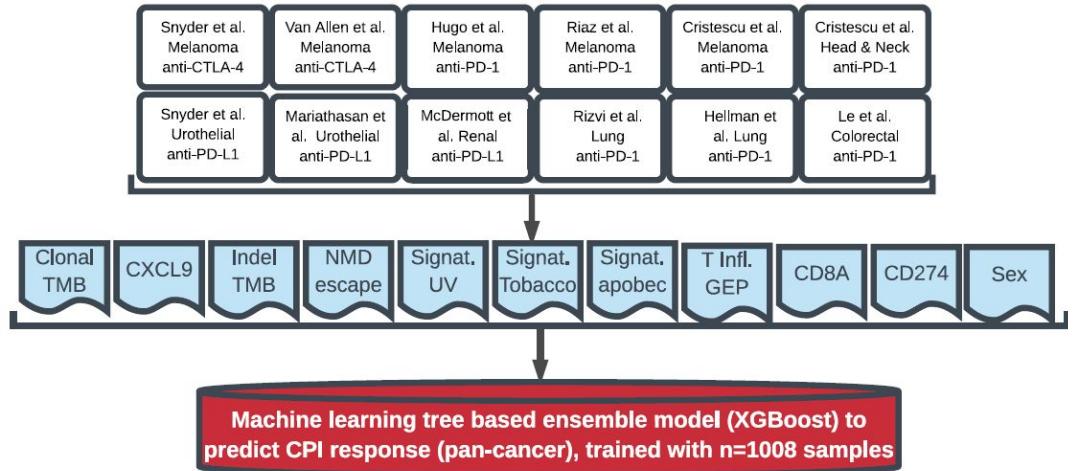
- From left to right: three patient cohorts (pan-cancer; head-and-neck cancer; melanoma)
- Open red circles: non responders; Black dots: responders.



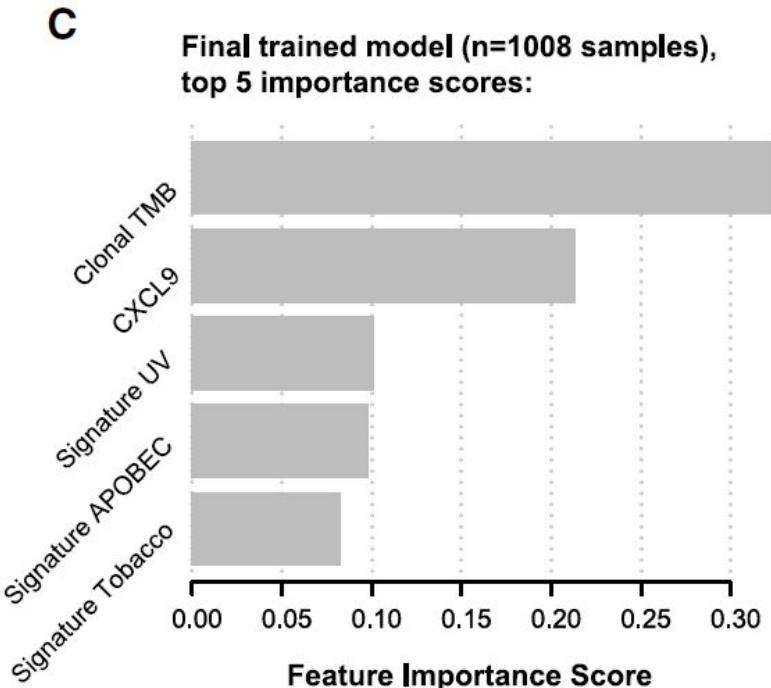
Data mining in public cancer database TCGA suggests potential indications



Meta-analysis (Litchfield et al. 2021) confirms TMB and T-cell infiltration as predictors of responsiveness

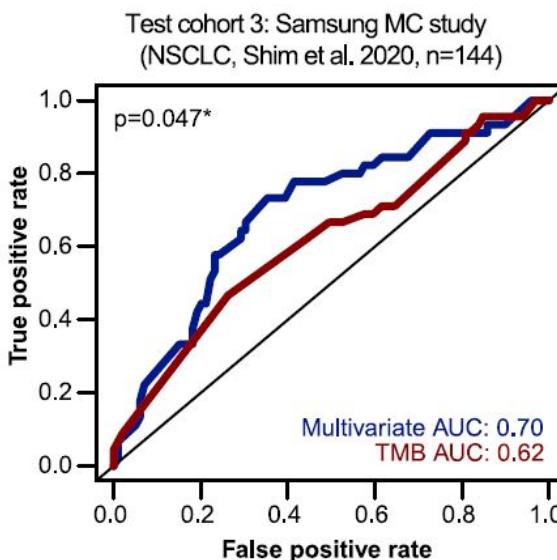
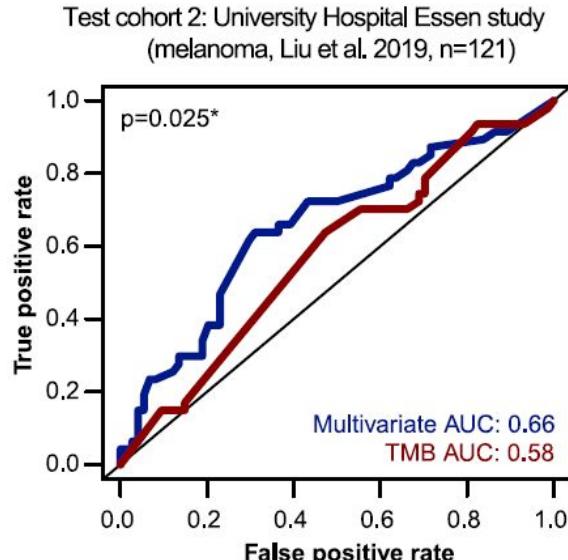
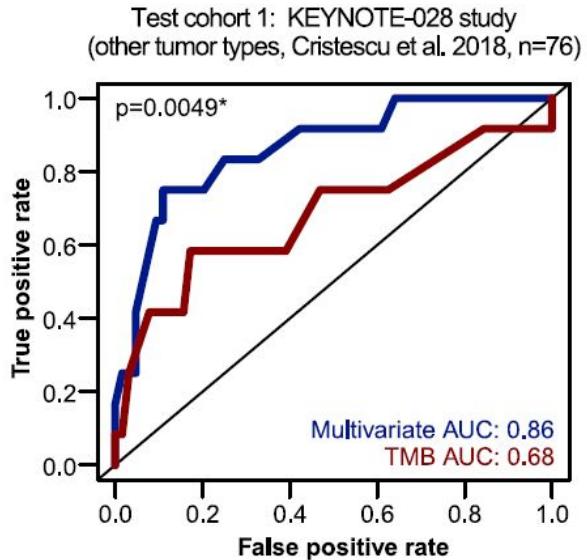


CXCL9 is a chemokine that enhances recruitment of cytotoxic CD8⁺ T cells into the tumor.



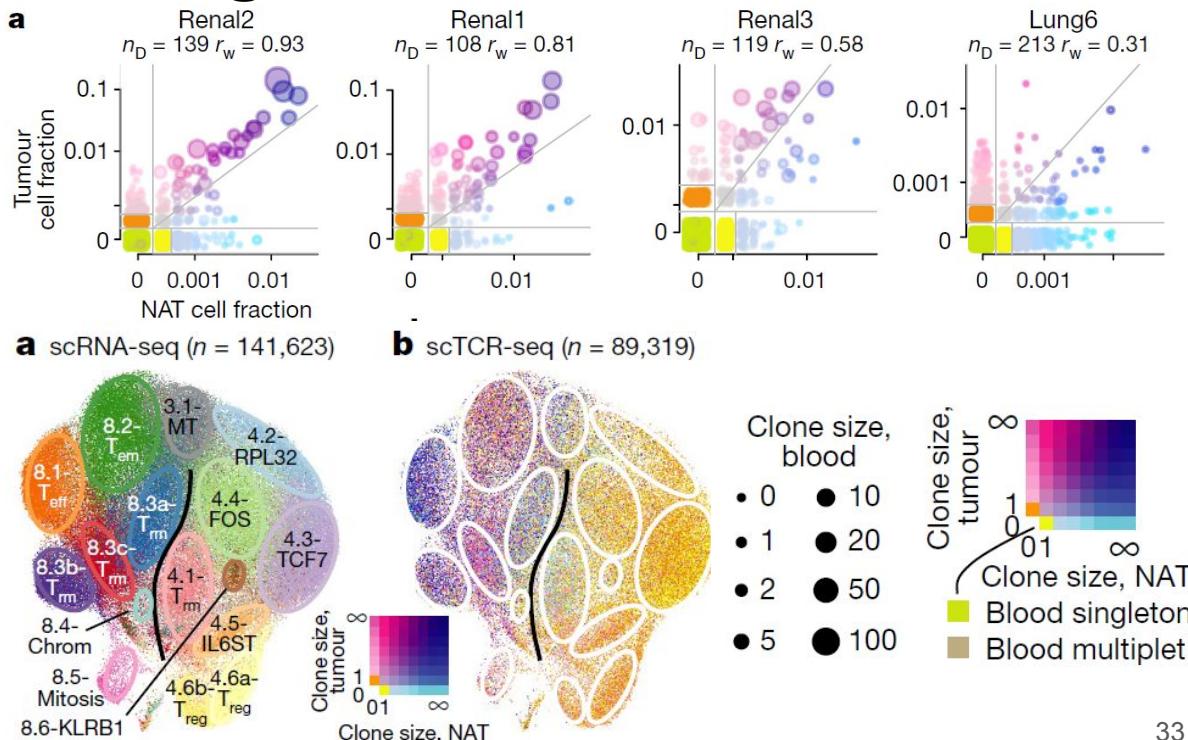
The multivariate classifier improves performance, but to predict responsiveness is an open question

Testing of TMB versus multivariable CPI stratifier performance in three independent test cohorts (total n=341):



Wu et al. characterized T cells in tumour, normal adjacent tissue (NAT), and blood using single-cell RNA and TCR sequencing

- Expanded clonotypes (T cells) found in the tumour and normal adjacent tissue can also typically be detected in peripheral blood.
- Intra-tumoural T cells, especially in responsive patients, are replenished with fresh, non-exhausted replacement cells from sites outside the tumour.



Caveats and challenge

- The curse of dimensionality
- Separation of mechanistic modelling and of statistical modelling
- Lack of causal models

Conclusions

- Biomarkers (1) guide compound optimization and differentiation in preclinical studies, (2) support human dose prediction in translational PK/PD studies, and (3) allow patient stratification in clinical trials;
- Mathematical and computational biology is indispensable for biomarker identification;
- Caveats in biomarker identification calls for integrated mechanistic and statistical modelling to establish causal relations.

Outline of lecture 12

- An example of integrating statistical and mechanistic modelling: Griffiths *et al.*
- Mechanistic modelling of biological systems: from Boolean network to Agent-based modelling
- Causal inference
- Where can we go from here

Integrating statistical with mechanistic modelling across scales

Integrating statistical with mechanistic modelling

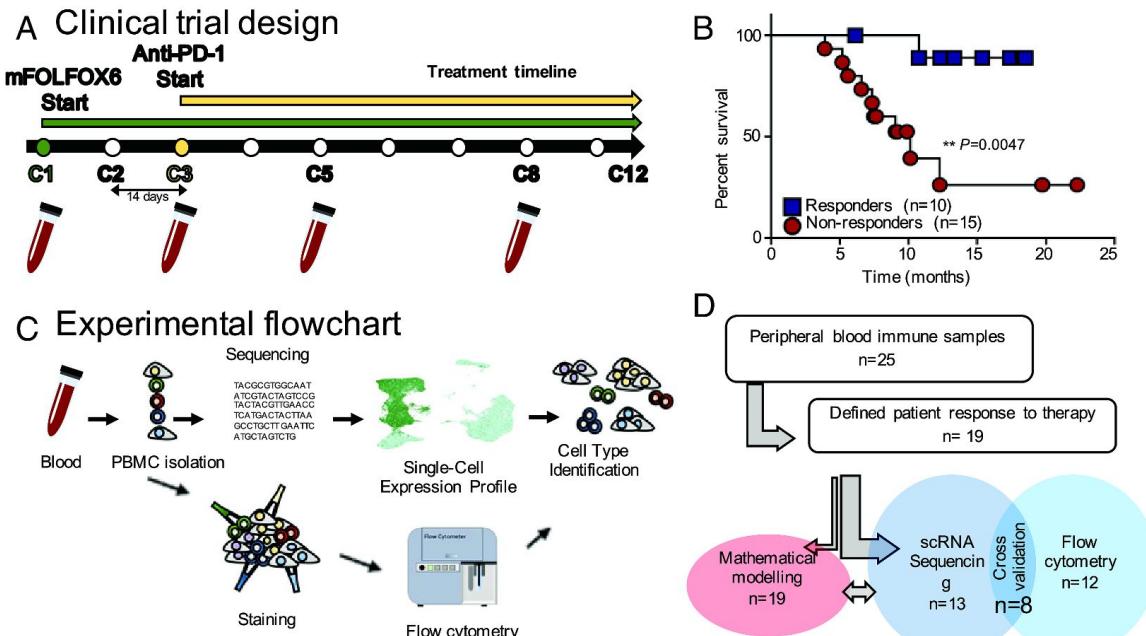
- Griffiths et al. (PNAS 2020) profiled peripheral immune cell abundance in time series following treatment of immunotherapy in a small clinical trial.
- The authors used mathematical modelling to characterize cell-cell interactions and analysed single-cell omics data to reveal immune cell abundance, pathway activity patterns, and differentiation status, which influence and are influenced by cell-cell interactions.
- The study presents an interesting case study that integrates statistical and mechanistic modelling on cellular- and omics-level and organ- and system-level.

How this study enriches our knowledge

- **Facts**
 - Clinical response to immune checkpoint inhibitors varies substantially.
 - Possible contributing factors correlate only weakly with patient response, including (1) tumor cell mutational load and antigen production, (2) immune-cell infiltration and signalling status, (3) Cross-talk between tumour and immune cells.
 - It is challenging to obtain tumour tissue samples.
- **Questions:** Can circulating immune cells serve as a surrogate measurement of a tumour's interaction with the host immune cells and reflect response to therapy early in the course of treatment?
- **Conclusions:** It is possible to predict patient response with the evolution of peripheral immune cell abundance and signalling over time, as well as how immune cell interact with the tumor.

Design of the clinical trial

- Gastrointestinal (GI) tumours
- mFOLFOX6 (modified FOLFOX6): a chemotherapy regimen.
- Patient response was assessed by RECIST (Response Evaluation Criteria in Solid Tumors) 1.1 guidelines, using computer tomography (CT).



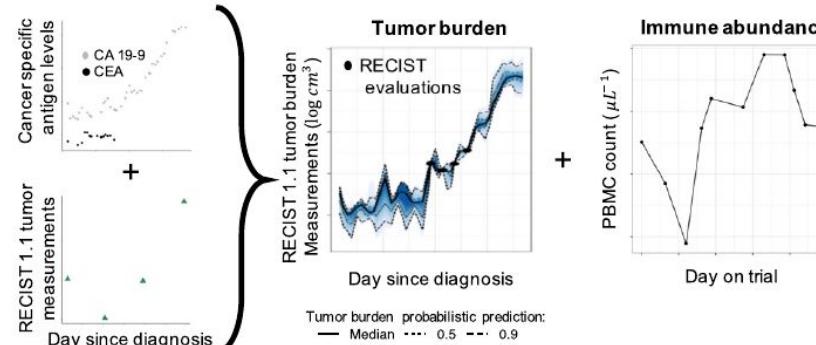
Mathematical modelling of tumour-immune cell interactions

Model inputs (all in time series):

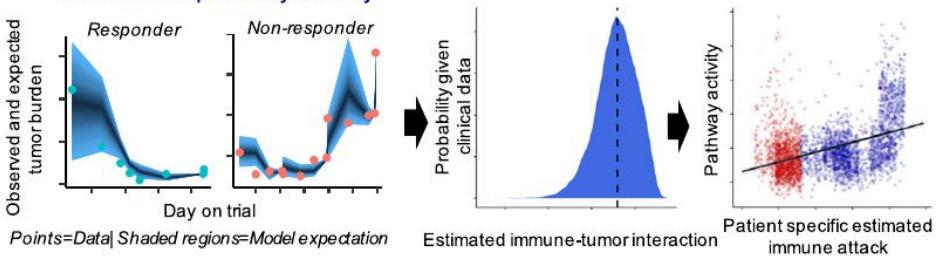
- Tumour burden, inferred by combining antigen values and RECIST evaluation with a *Gaussian process latent variable model*.
- Abundance of PBMCs

Model output: estimated ability of immune cells to kill tumour cells

- E Mathematical model flowchart: tumor-immune cell interactions
- i) Construct time course of tumor and immune abundance for each patient:



- ii) Model how strongly immune cells interact and attack tumor and correlate to pathway activity:



Gaussian Process

The Lotka-Volterra model of predator-prey relationships

- The Lotka-Volterra equations modelling predator-prey relationships.

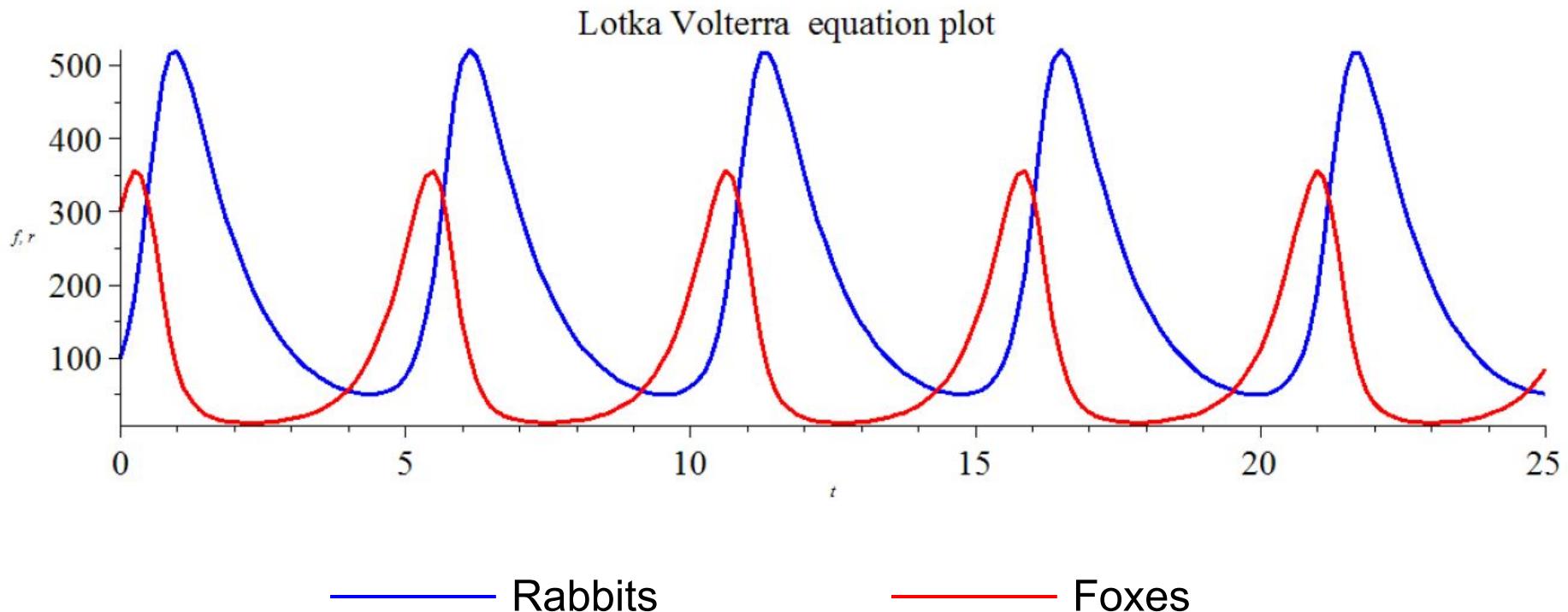
$$\frac{dx}{dt} = \alpha x - \beta xy, \tag{1}$$

$$\frac{dy}{dt} = -\gamma y + \delta xy, \tag{2}$$

where

- x is the number of prey (*e.g.* rabbits),
- y is the number of predator (*e.g.* foxes),
- $\frac{dx}{dt}$ and $\frac{dy}{dt}$ represent growth rates of the two populations,
- t represents time,
- α, β, γ , and δ are real parameters specifying the interaction of the two species.

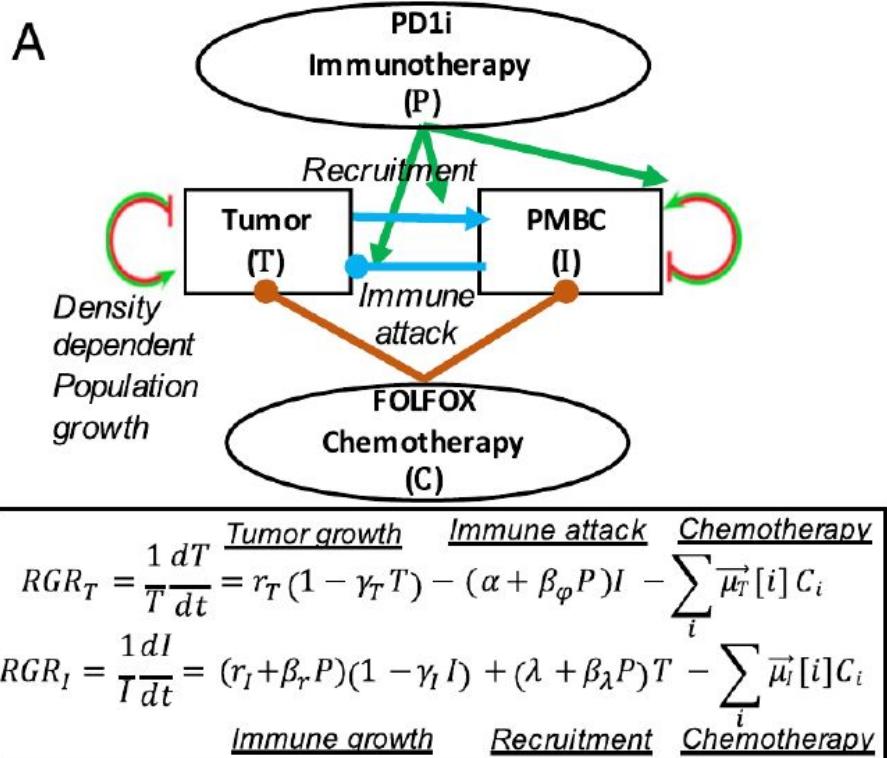
The Lotka-Volterra equations, visualized



Modelling of interactions between tumour and immune cells

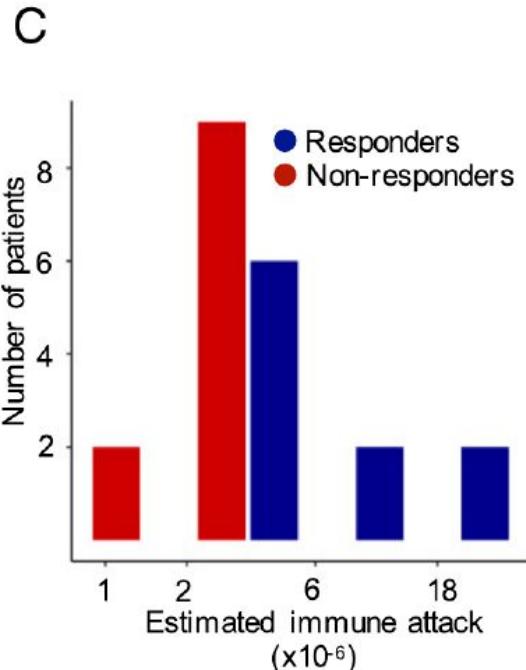
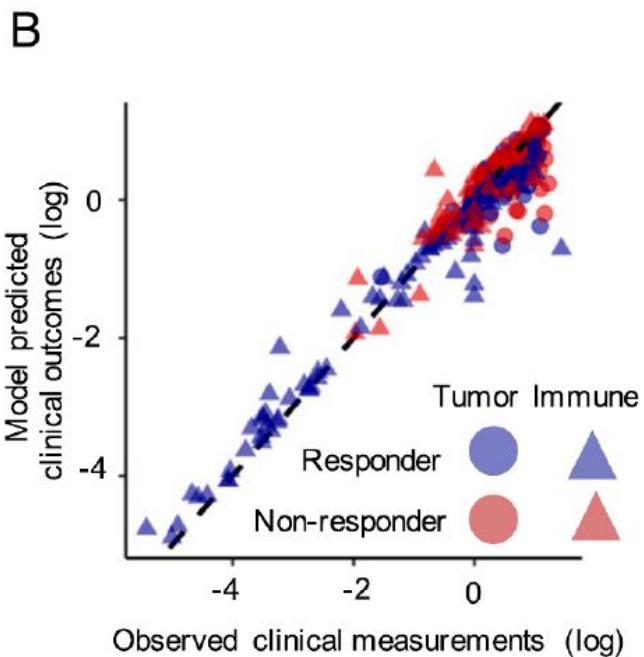
Modelling assumptions:

- Tumor cells are attacked by immune cells
- Tumor cells recruits immune cells
- Chemotherapy kills both tumour and immune cells
- Anti-PD1 inhibitor immunotherapy impacts immune proliferation, recruitment, and cytotoxic tumor activity.



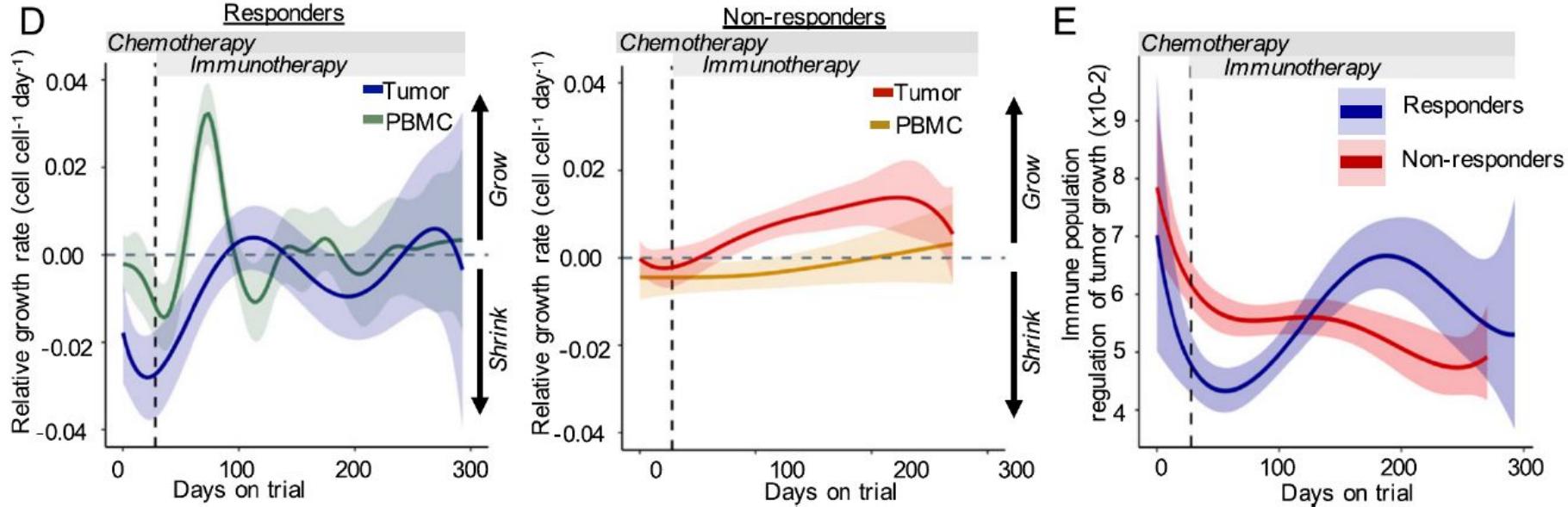
Model prediction and performance

- The strength of immune-tumor interaction is estimated by statistically fitting the growth rate of immune cells and tumor size to model predictions.
- Changes in tumor burden and immune cell abundance are described by data fitting, using a *Bayesian hierarchical approach*.



Multilevel/hierarchical models

Profiles of relative growth rates differ between responders and non-responders

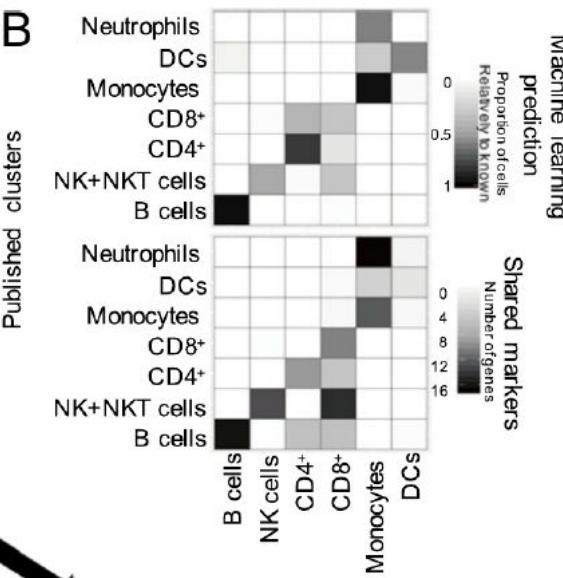
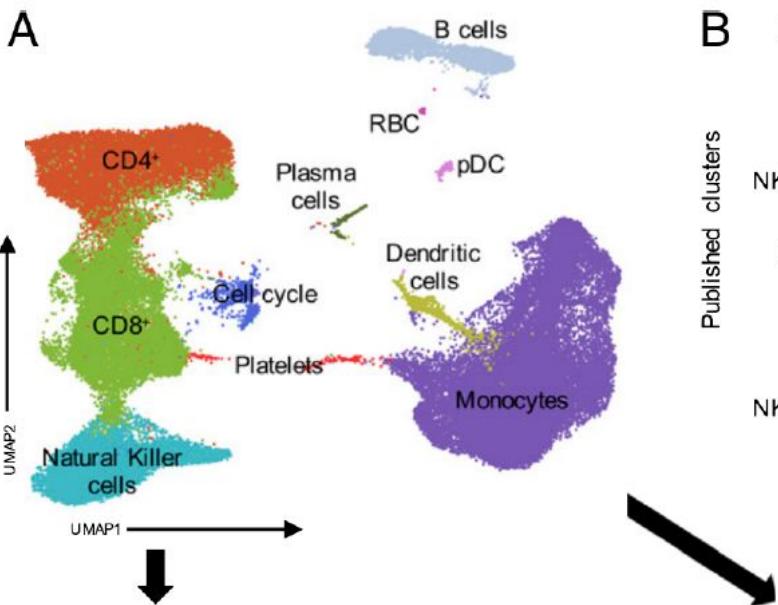


- Neither tumor nor PBMC responds to chemotherapy in non-responders.
- Responders have lower PBMC abundance in general at baseline.

Immune cell population identified by scRNASeq

PBMCs were analysed at three time points:

1. Cycle 1 (C1): baseline before treatment;
2. Cycle 3 (C3): chemotherapy alone;
3. Cycle 5 (C5): chemotherapy + anti-PD-1.

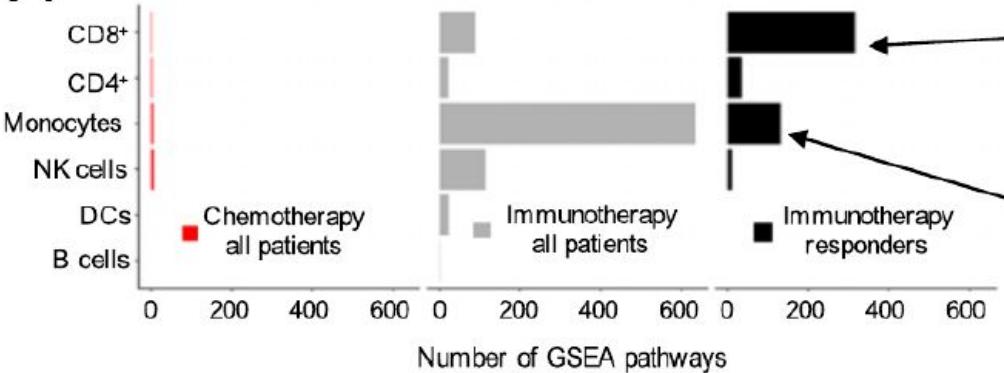


A total number of 70781 cells from 13 patients (7 responders and 6 non-responders) were profiled.

Pathway analysis

Single-sample gene-set enrichment analysis was performed to identify pathway differences before therapy, during chemotherapy, and during the early combo of chemotherapy and immunotherapy using a *random effects linear model*.

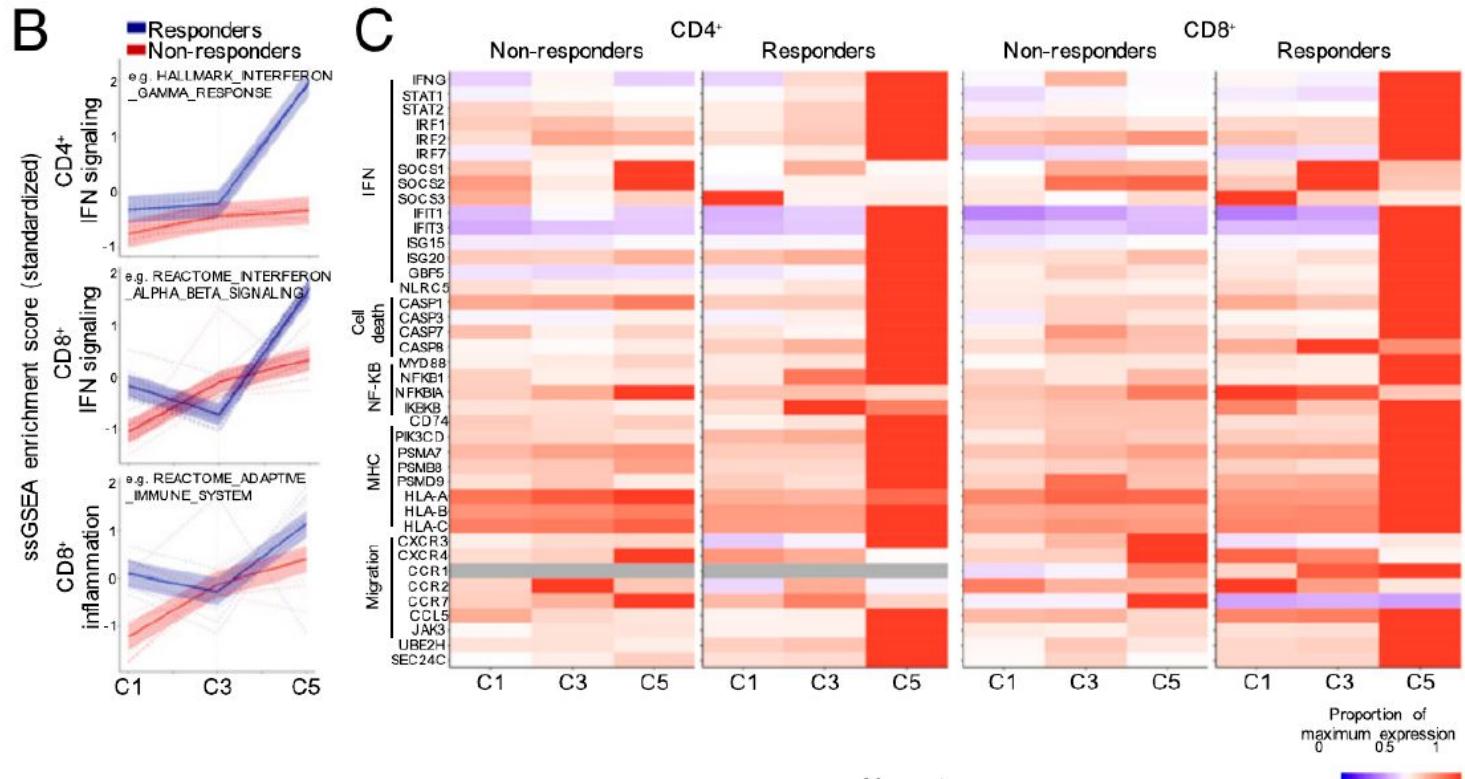
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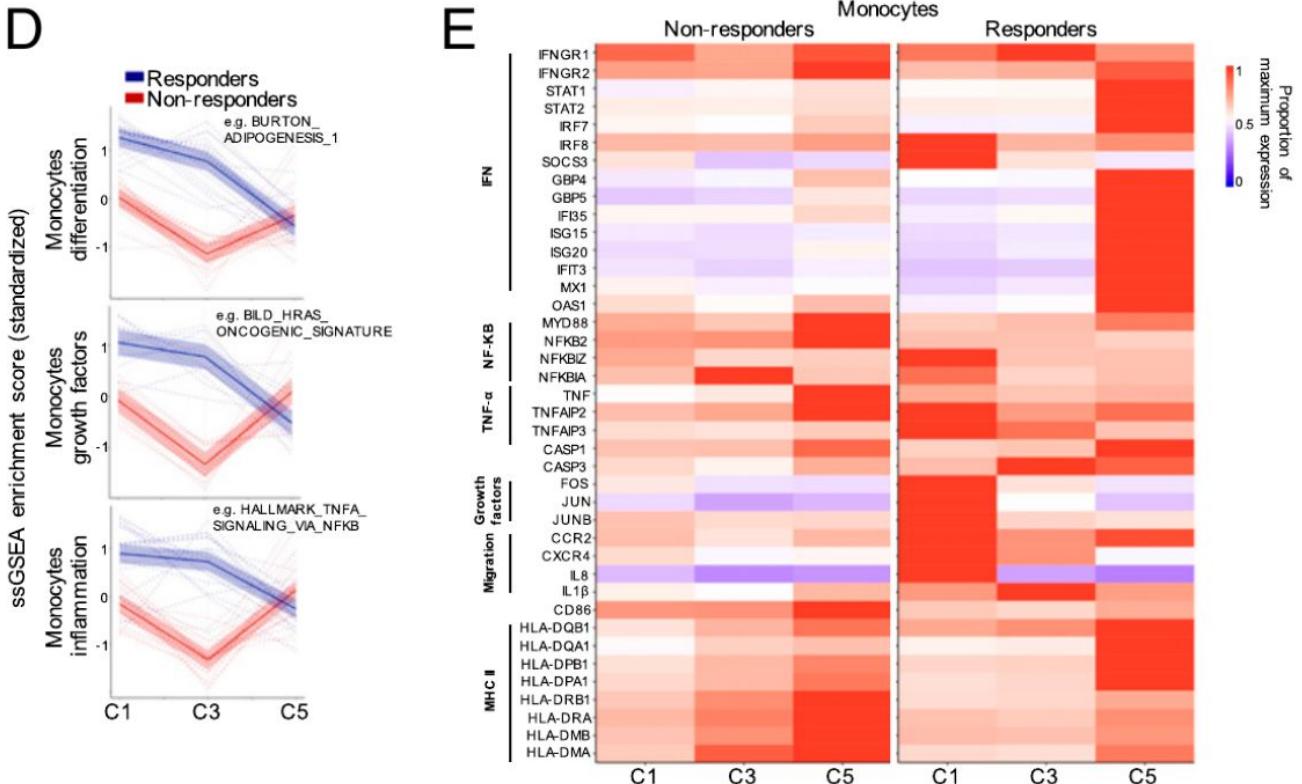
Examples

- HALLMARK_INTERFERON_GAMMA_RESPONSE
- HALLMARK_INTERFERON_ALPHA_RESPONSE
- HECKER_IFNB1_TARGETS
- REACTOME_INTERFERON_ALPHA_BETA_SIGNALING
- BROWNE_INTERFERON_RESPONSIVE_GENES
- ZHANG_INTERFERON_RESPONSE
- BILD_HRAS_ONCOGENIC_SIGNATURE
- ZWANG_CLASS_3_TRANSIENTLY_INDUCED_BY_EGF
- NAGASHIMA_EGF_SIGNALING_UP
- BURTON_ADIPOGENESIS_1
- NAGASHIMA_NRG1_SIGNALING_UP
- RIZ_ERYTHROID_DIFFERENTIATION_12HR

Responders show changes in T-cell signalling during treatment

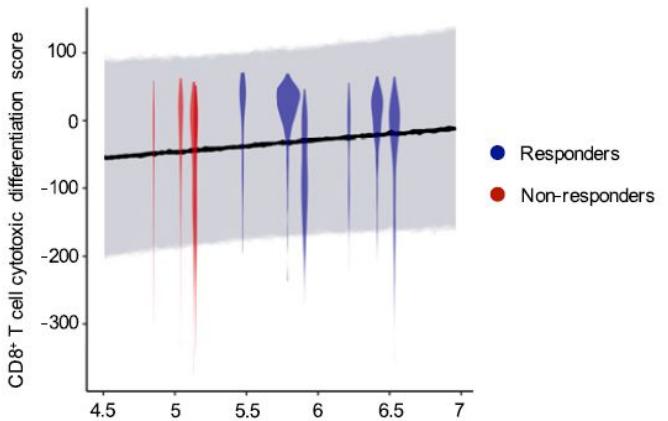
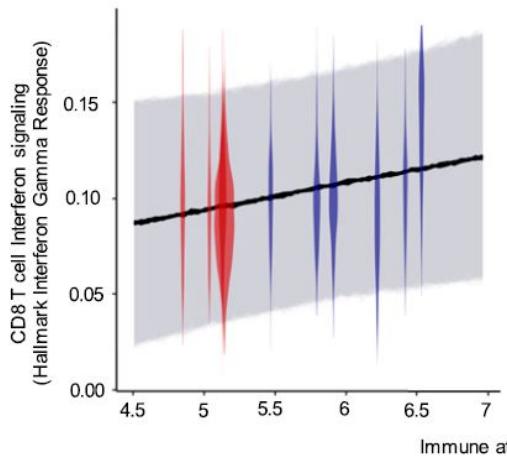


Responders show changes in monocyte signalling during treatment

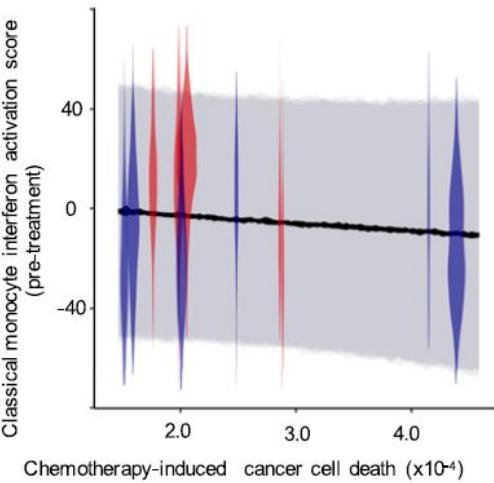


Associations between omics data and inferred model parameter

D



E



Impact and limitation of the study

- *On the biological side*, the results suggest that peripheral blood phenotypes can be used as biomarker of patient responsiveness to therapy. The idea seems to be confirmed the findings by Wu *et al.*, *Peripheral T cell expansion predicts tumour infiltration and clinical response*, Nature 2020.
- *On the modelling side*, the study integrates machine learning, omics data analysis, mathematical modelling techniques to link macroscopic findings, for instance antigen and RECIST scores, with cellular findings, including scRNASeq and flow cytometry. This study exemplifies what we call *multiscale modelling of drug mechanism and safety*.
- We do not know why some patients respond to anti-PD-1 or anti-PDL1 therapies better than other patients based on findings reported in both papers. Nevertheless, both studies suggest that immune cells in peripheral blood may be used as biomarkers in certain settings.

Bonus: Mathematical modelling of epidemiology

The SIR (S =susceptible, I =infectious, R =removed) model modelling epidemiology (without viral dynamics, $N = S + I + R$).

$$\frac{dS}{dt} = -\frac{\beta IS}{N}, \quad (3)$$

$$\frac{dI}{dt} = \frac{\beta IS}{N} - \gamma I, \quad (4)$$

$$\frac{dR}{dt} = \gamma I \quad (5)$$

Agent-based modelling

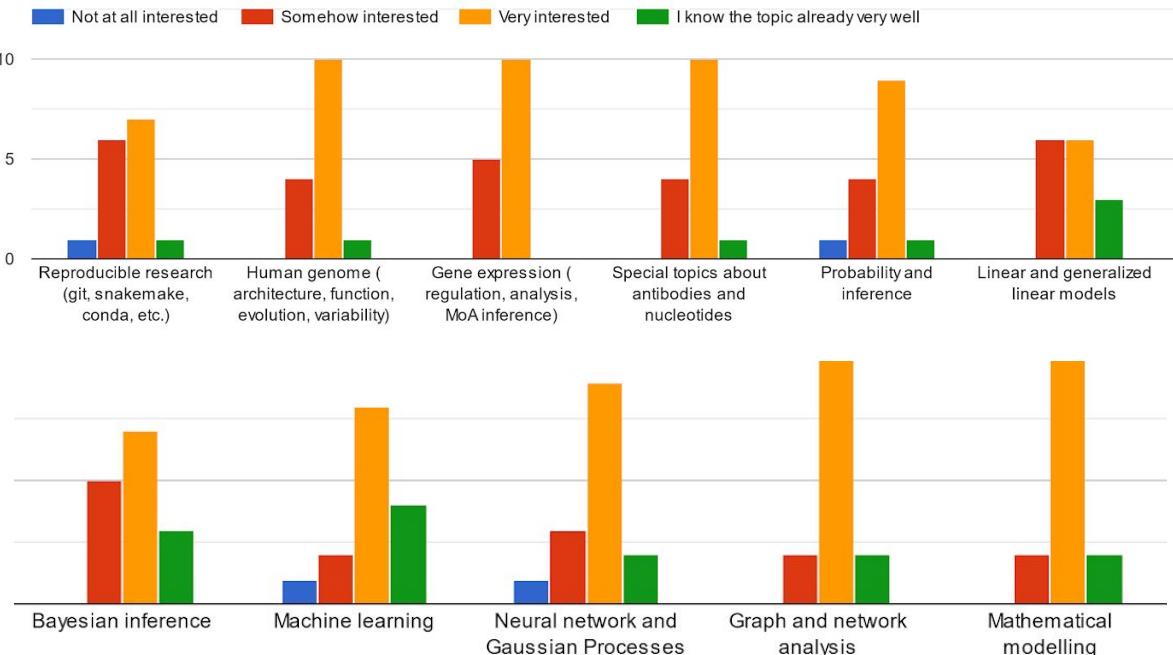
Bradford Hill Criteria for causation

1. **Strength** (effect size)
2. **Consistency** (reproducibility)
3. ***Specificity***
4. **Temporality**
5. **Biological gradient** (dose-response relationship)
6. ***Plausibility***
7. **Coherence**
8. **Experiment**
9. **Analogy** (similarity)
10. **Reversibility (proposed by others)**

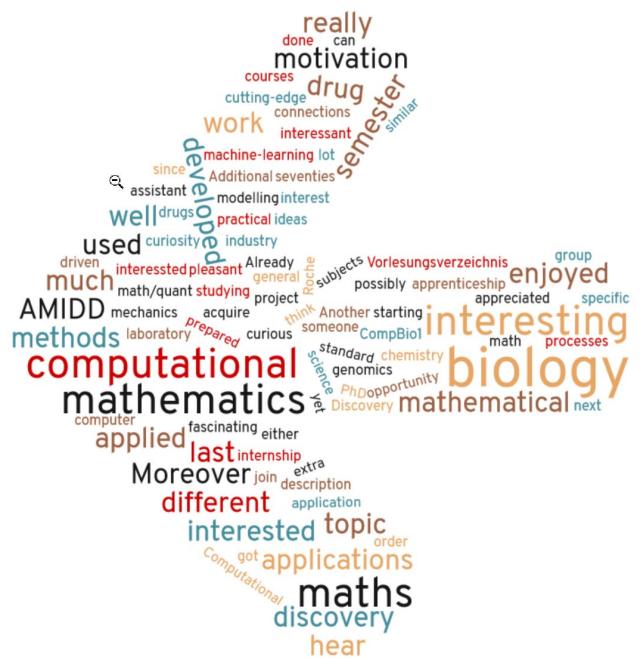
Statistical causal inference with Directed Acyclic Graphs (DAGs)

Where can we learn next?

- *iBiology*, freely available at <https://www.ibiology.org/>
- *Nature Reviews Drug Discovery*, <https://www.nature.com/nrd/>
- Blogs [In the Pipeline](#) by Derek Lowe and [CureFFI](#) by Eric Minikel
- *Statistical Rethinking* by Richard McElreath, [with lecture videos on YouTube](#)
- *Information Theory, Inference, and Learning Algorithms* by David MacKay, [with lecture videos on YouTube](#).



Your interest and motivation motivate me



A cloud of positive words including motivation, interest, biology, and related concepts.

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Clonality and immuno-genicity of cancer cells influence efficacy of cancer immunotherapy

